Introduction to Deep Learning

CSI 5180 - Machine Learning for Bioinformatics

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Preamble

Quote of the Day

Summary

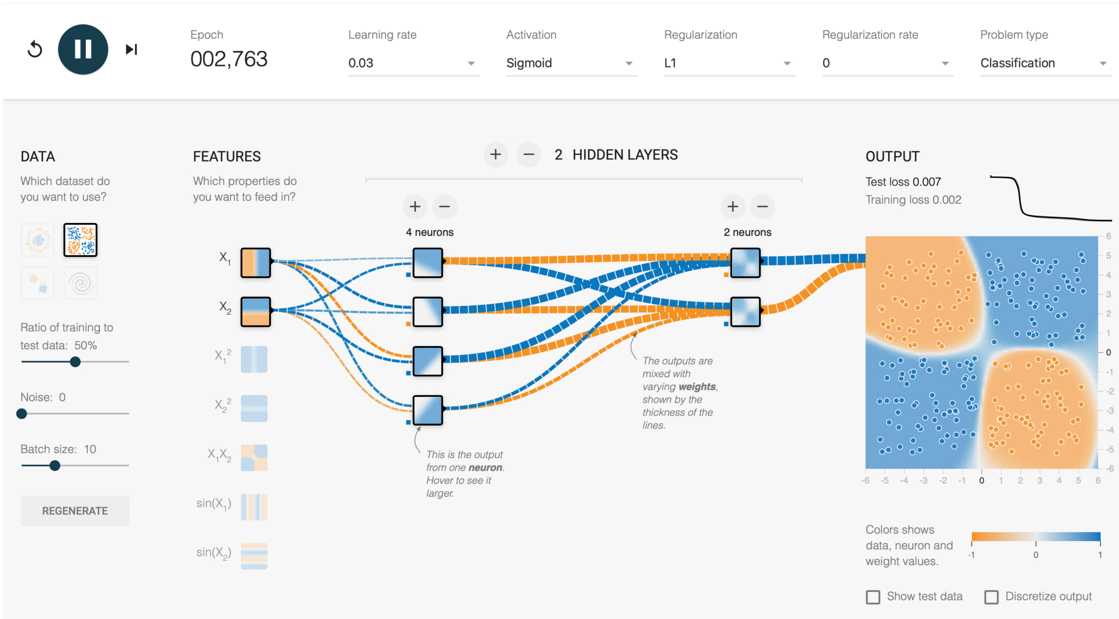
Neural networks evolved from simple, biologically inspired perceptrons to **deep**, **multilayer** architectures that rely on **nonlinear activation functions** for learning complex patterns. The **universal approximation theorem** underpins their ability to approximate any continuous function, and modern frameworks like **PyTorch**, **TensorFlow**, and **Keras** enable practical deep learning applications.

Learning Objectives

- **Explain** basic neural network models (perceptrons and MLPs) and their computational foundations.
- **Appreciate** the limitations of single-layer networks and the necessity for hidden layers.
- **Describe** the role and impact of nonlinear activation functions (sigmoid, tanh, ReLU) in learning.
- **Articulate** the universal approximation theorem and its significance.
- **Implement** and evaluate deep learning models using modern frameworks such as TensorFlow and Keras.

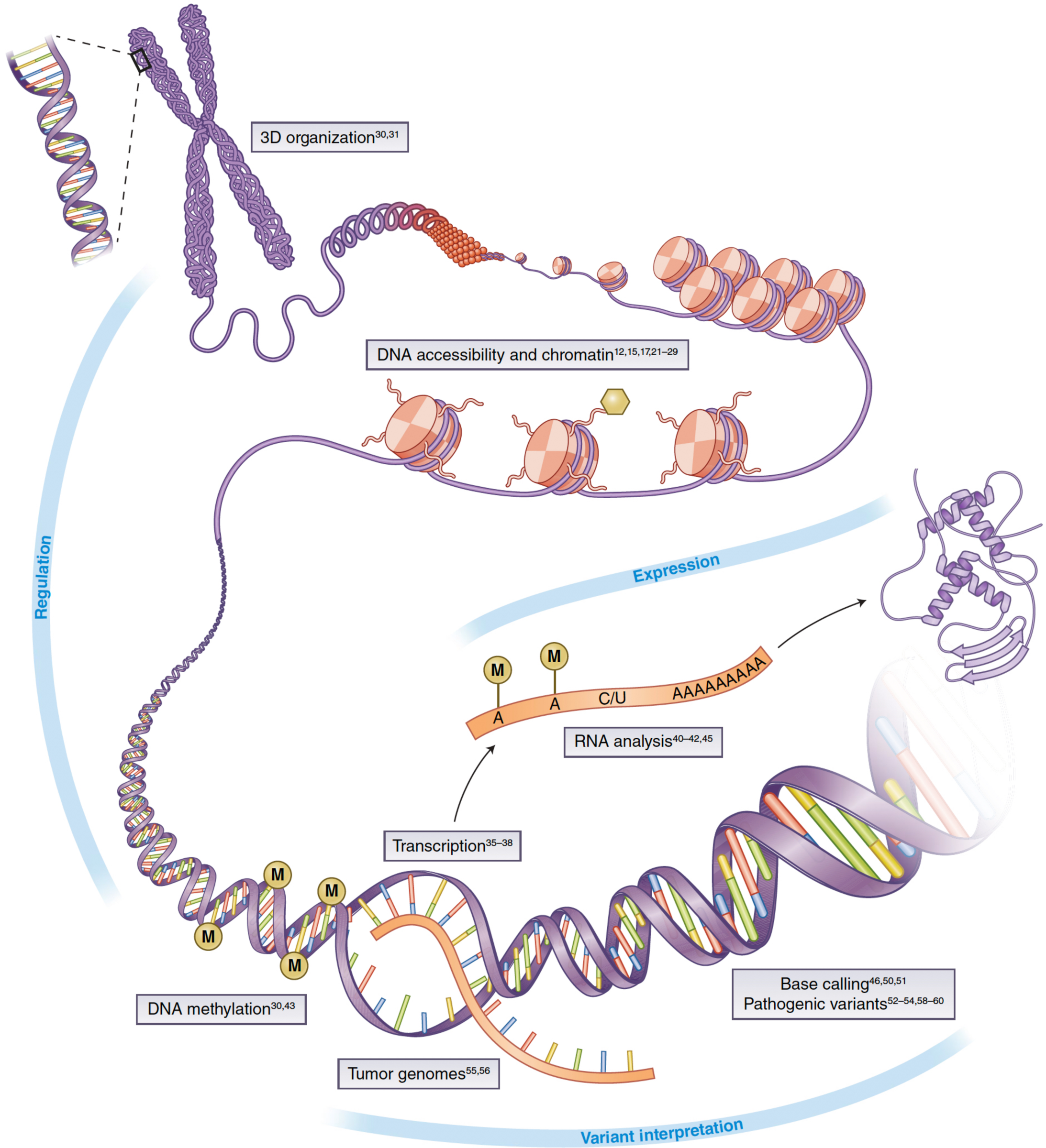
Introduction

TensorFlow Playground



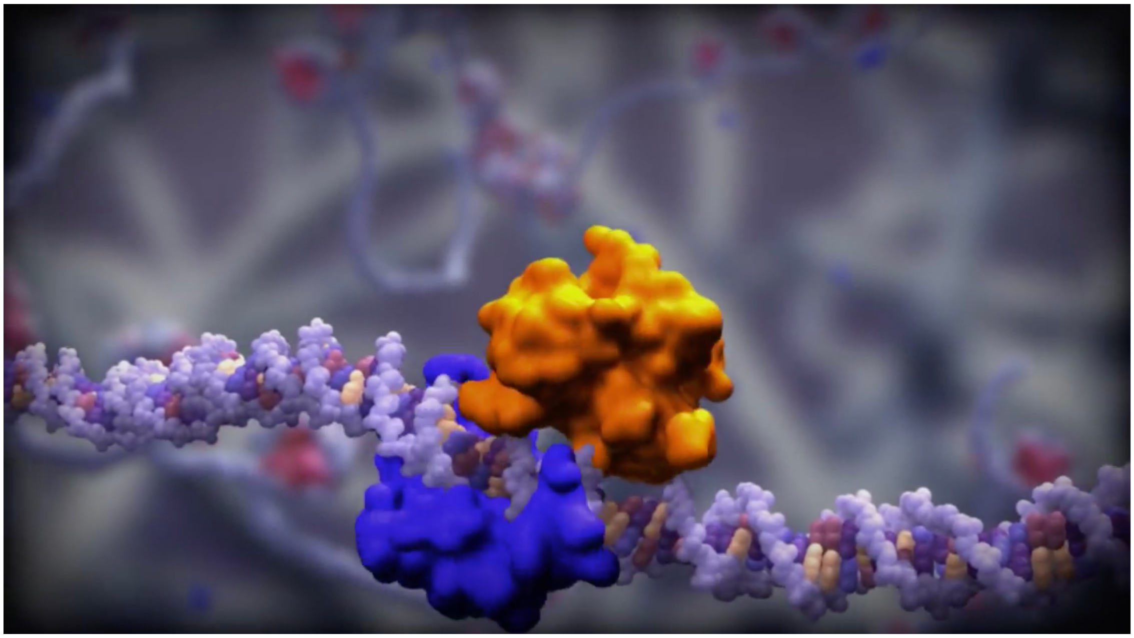
playground.tensorflow.org

Primer on Deep Learning in Genomics



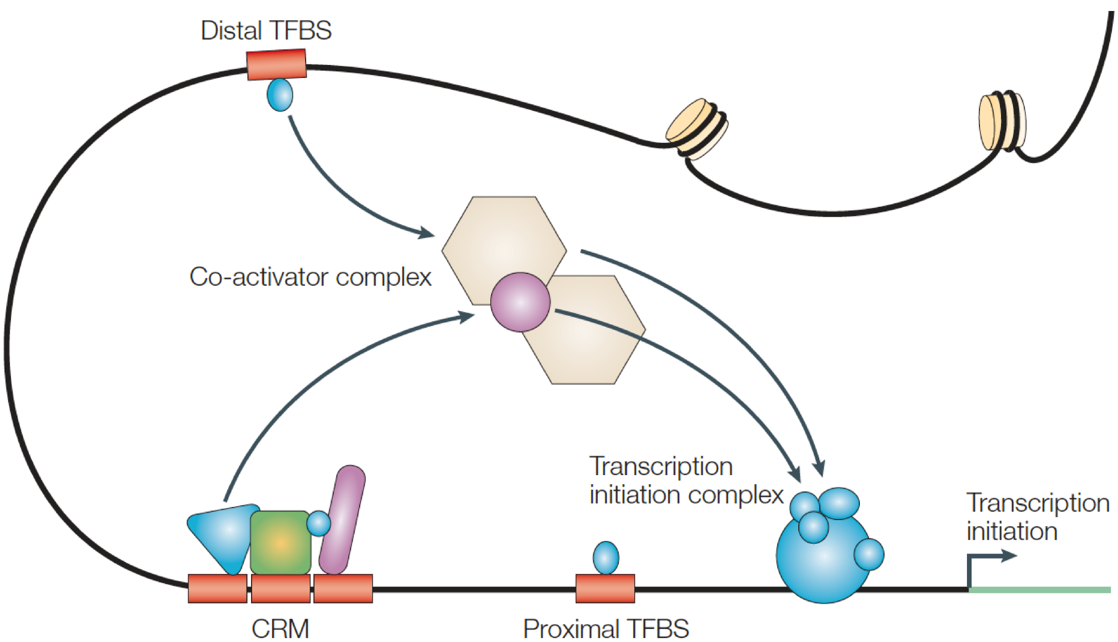
Zou et al. (2019), Figure 2

Transcription Factors



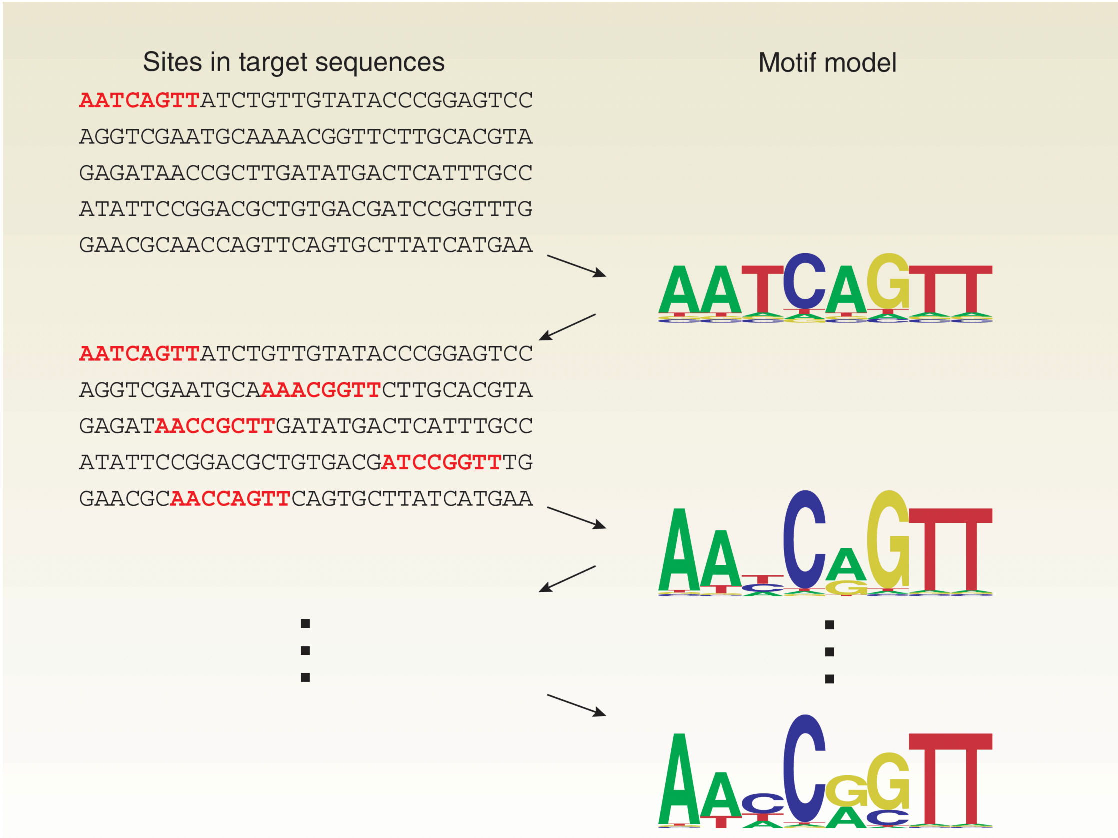
See: https://youtu.be/MkUgkDLp2iE

Gene Regulation



Wasserman and Sandelin (2004)

DNA Sequence Motif Discovery



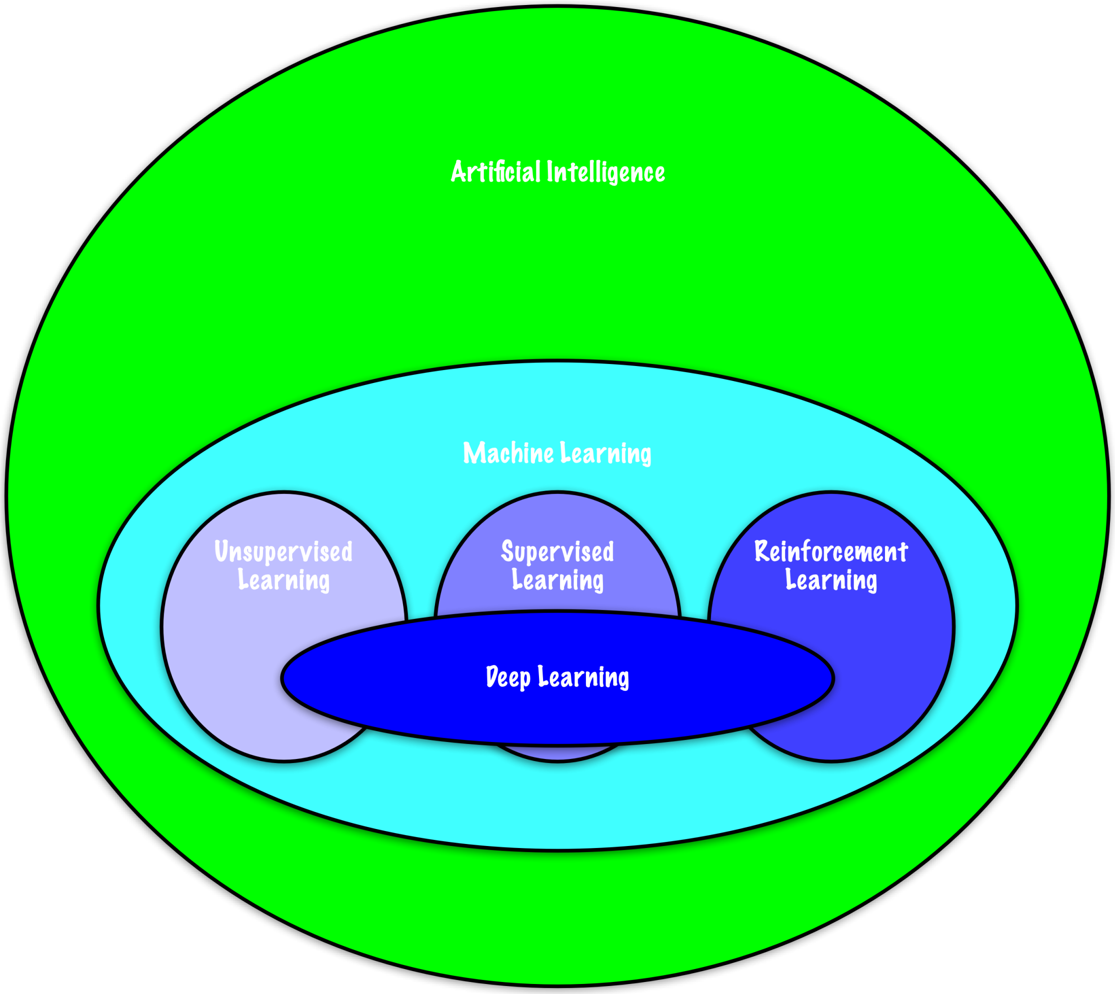
D’haeseleer (2006)

Deep Learning in Genomics Primer

- James Zou, Mikael Huss, Abubakar Abid, Pejman Mohammadi, Ali Torkamani, and Amalio Telenti, A primer on deep learning in genomics, *Nat Genet* **51**:1, 12–18, 2019.
    - Google Colab Notebook

Zou et al. (2019)

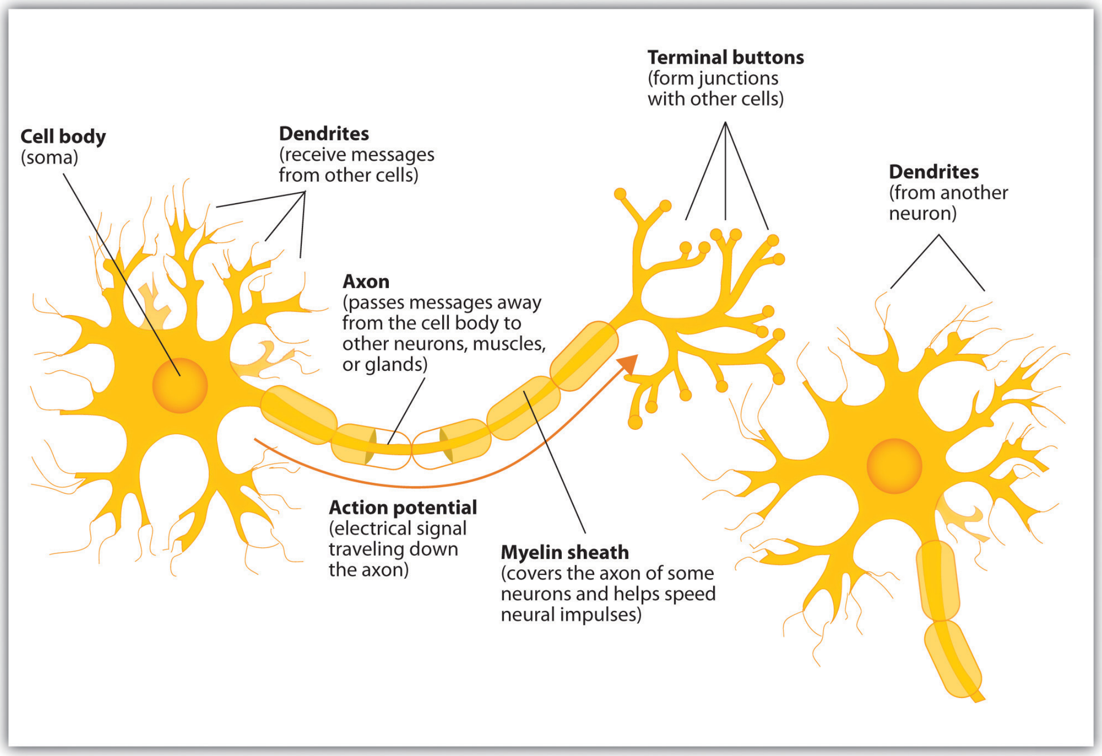
Machine Learning Problems



- **Supervised Learning**: Classification, Regression
- **Unsupervised Learning**: Autoencoders, Self-Supervised
- **Reinforcement Learning**: Now an Integral Component

We will begin our exploration within the framework of supervised learning.

A Neuron



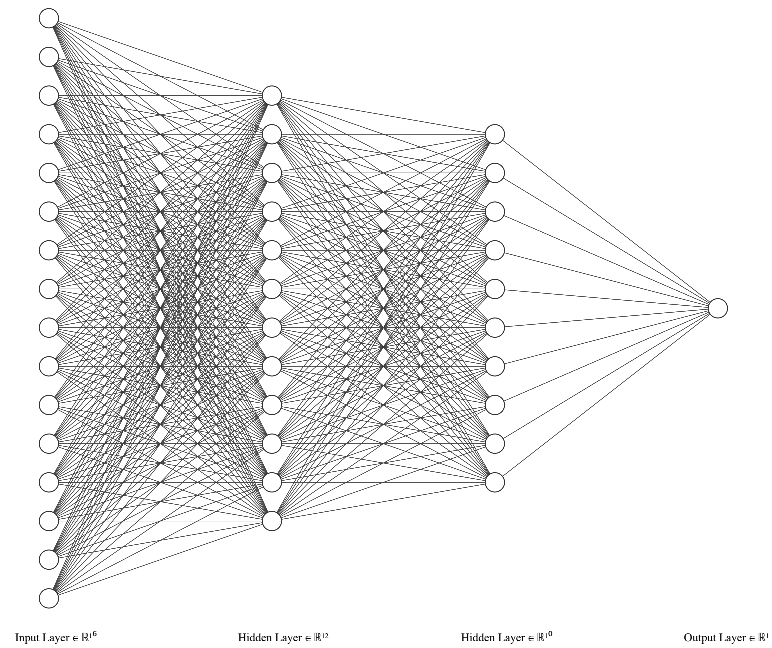
Attribution: Jennifer Walinga, CC BY-SA 4.0

In the study of artificial intelligence, it is logical to derive inspiration from the most well-understood form of intelligence: the human brain. The brain is composed of a complex network of neurons, which together form biological neural networks. Although each neuron exhibits relatively simple behavior, it is connected to thousands of other neurons, contributing to the intricate functionality of these networks.

A neuron can be conceptualized as a basic computational unit, and the complexity of brain function arises from the interconnectedness of these units.

Yann LeCun and other researchers have frequently noted that artificial neural networks used in machine learning resemble biological neural networks in much the same way that an airplane's wings resemble those of a bird.

Connectionist



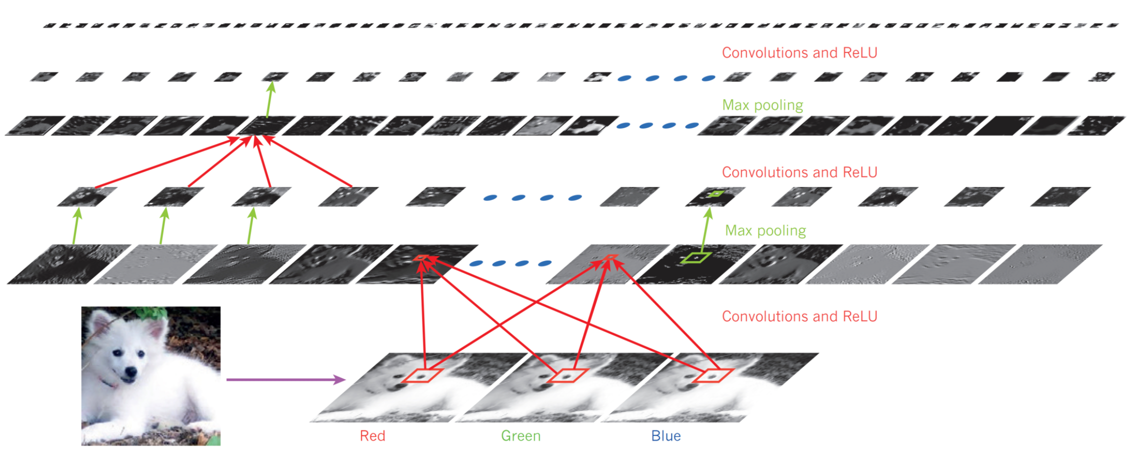
Attribution: LeNail, (2019). NN-SVG: Publication-Ready Neural Network Architecture Schematics. Journal of Open Source Software, 4(33), 747, https://doi.org/10.21105/joss.00747 (GitHub)

A characteristic of biological neural networks that we adopt is the organization of neurons into layers, particularly evident in the cerebral cortex.

Neural networks (**NNs**) consist of layers of **interconnected nodes (neurons)**, each **connection** having an associated **weight**.

Neural networks process input data through these weighted connections, and **learning** occurs by **adjusting the weights** based on **errors** in the **training data**.

Hierarchy of Concepts



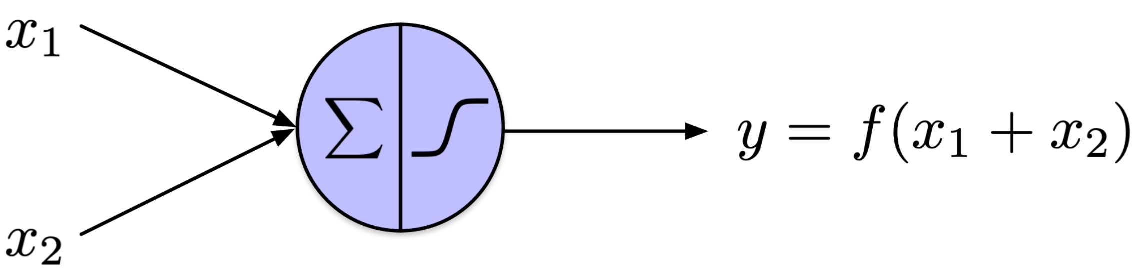
Attribution: LeCun, Bengio, and Hinton (2015)

In the book “Deep Learning” (Goodfellow, Bengio, and Courville 2016), authors Goodfellow, Bengio, and Courville define deep learning as a subset of machine learning that enables computers to “understand the world in terms of a hierarchy of concepts.”

This hierarchical approach is one of deep learning’s most significant contributions. It reduces the need for manual feature engineering and redirects the focus toward the engineering of neural network architectures.

Basics

Computations with Neurodes



where $x_1, x_2 \in \{0,1\}$ and $f(z)$ is an **indicator function**:

$$ f(z)= \begin{cases}0, & z<\theta \\ 1, & z \geq \theta\end{cases} $$

McCulloch and Pitts (1943) termed artificial neurons, **neurodes**, for **“neuron”** + **“node”**.

In mathematics, $f(z)$, as defined above, is known as an **indicator function** or a **characteristic function**.

These neurodes have one or more binary inputs, taking a value of 0 or 1, and one binary output.

They showed that such units could implement Boolean functions such as **AND**, **OR**, and **NOT**.

But also that networks of such units can compute any logical proposition.

Computations with Neurodes

$$ y = f(x_1 + x_2)= \begin{cases}0, & x_1 + x_2 <\theta \\ 1, & x_1 + x_2 \geq \theta\end{cases} $$

- With $\theta = 2$, the neurode implements an **AND** logic gate.
- With $\theta = 1$, the neurode implements an **OR** logic gate.

More **complex logic** can be constructed by multiplying the inputs by **-1**, which is interpreted as **inhibitory**. Namely, this allows building a logical NOT.

With $\theta = 1$, $x_1 {1} and x_2 multiplied by (-1), $y = 0$ when $x_2 = 1$, $y = 1$, if $x_2 = 0$.

$$ y = f(x_1 + (-1) x_2)= \begin{cases}0, & x_1 + x_2 <\theta \\ 1, & x_1 + (-1) x_2 \geq \theta\end{cases} $$

Neurons can be broadly categorized into two primary types: **excitatory** and **inhibitory**.

Computations with Neurodes

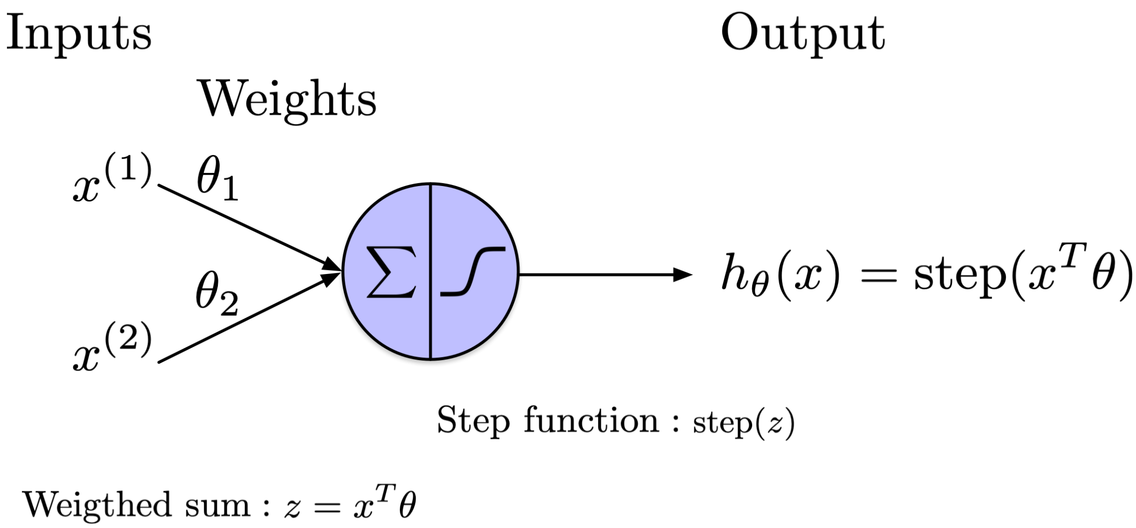
- **Digital computations** can be broken down into a **sequence of logical operations**, enabling neurode networks to **execute any computation**.
- McCulloch and Pitts (1943) did **not** focus on **learning** parameter θ.
- They introduced a machine that **computes any function** but **cannot learn**.

The period roughly from 1930 to 1950 marked a transformative shift in mathematics toward the formalization of computation. Pioneering work by **Gödel**, **Church**, and **Turing** not only established the theoretical limits and capabilities of computation—with Gödel’s **incompleteness theorems**, Church’s **λ-calculus and thesis**, and Turing’s model of **universal machines**—but also set the stage for later developments in computer science.

McCulloch and Pitts’ 1943 model of neural networks was inspired by this early mathematical framework linking computation to aspects of intelligence, prefiguring later research in artificial intelligence.

From this work, we take the idea that networks of such units perform computations. Signal propagates from one end of the network to compute a result.

Threshold Logic Unit



Rosenblatt (1958)

In 1957, Frank Rosenblatt developed a conceptually distinct model of a neuron known as the **threshold logic unit**, which he published in 1958.

In this model, both the inputs and the output of the neuron are represented as **real values**. Notably, each input connection has an associated weight.

The left section of the neuron, denoted by the sigma symbol, represents the computation of a weighted sum of its inputs, expressed as $\theta_1 x_1 + \theta_2 x_2 + \ldots + \theta_D x_D + b$.

This sum is then processed through a step function, right section of the neuron, to generate the output.

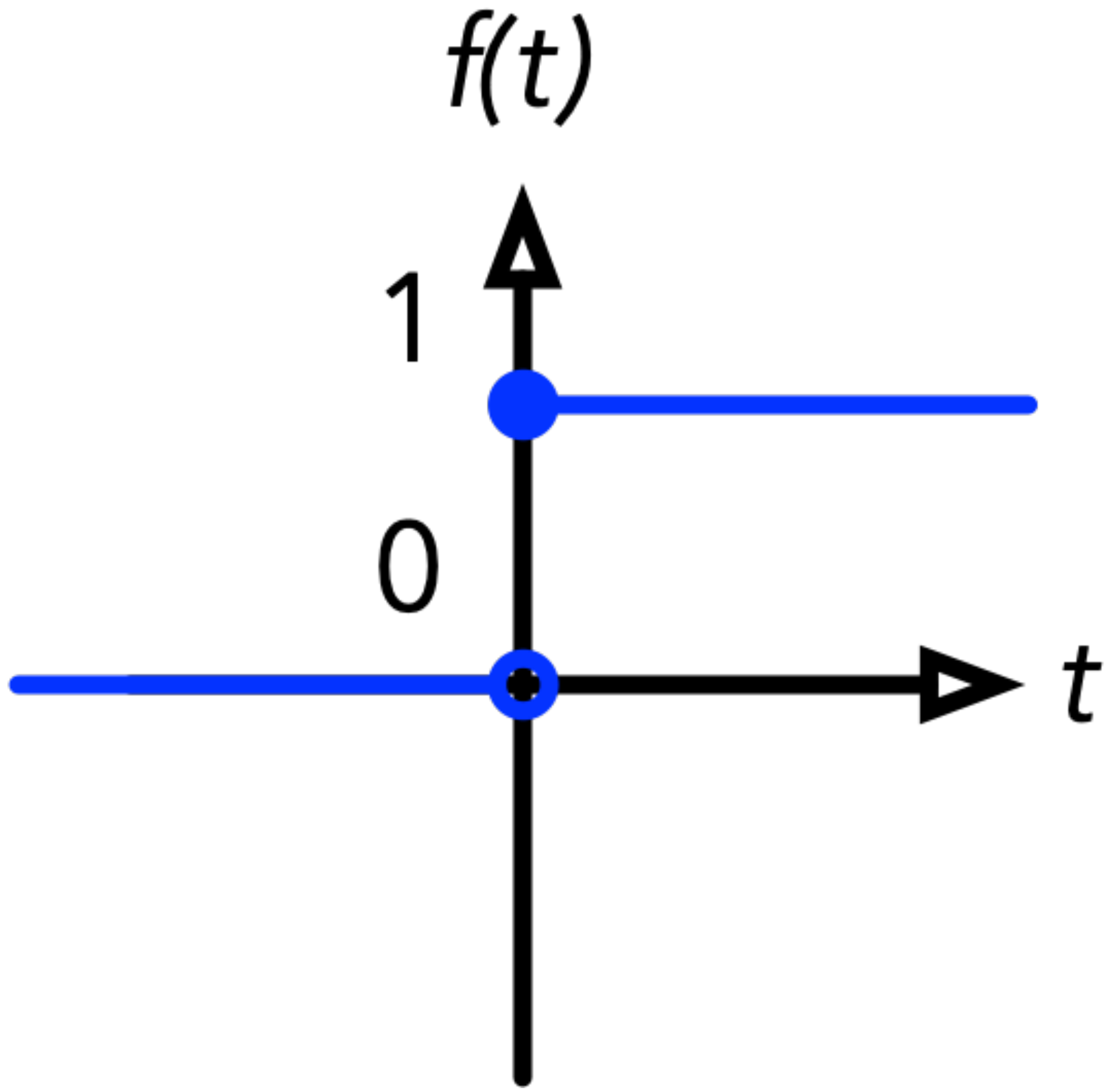
Here, $x^T \theta$ represents the dot product of two vectors: x and θ. Here, x^T denotes the transpose of the vector x, converting it from a row vector to a column vector, allowing the dot product operation to be performed with the vector θ.

The dot product $x^T \theta$ is then a scalar given by:

$$ x^T \theta = x^{(1)} \theta_1 + x^{(2)} \theta_2 + \cdots + x_{(D)} \theta_D $$

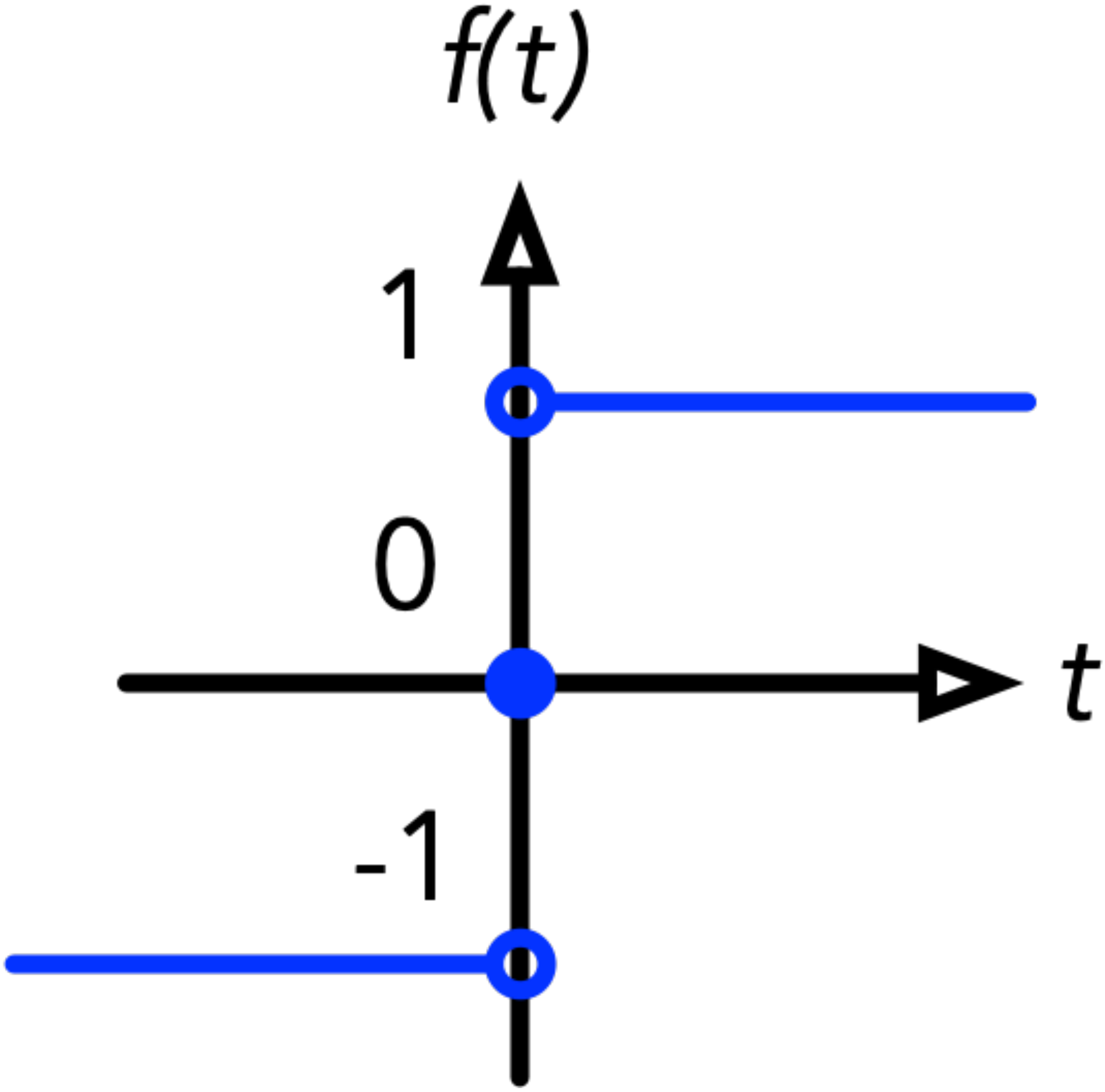
where $x^{(j)}$ and $theta_j$ are the components of the vectors x and θ, respectively.

Simple Step Functions



$\text{heaviside}(t)$ =

- 1, if $t \geq 0$
- 0, if $t < 0$

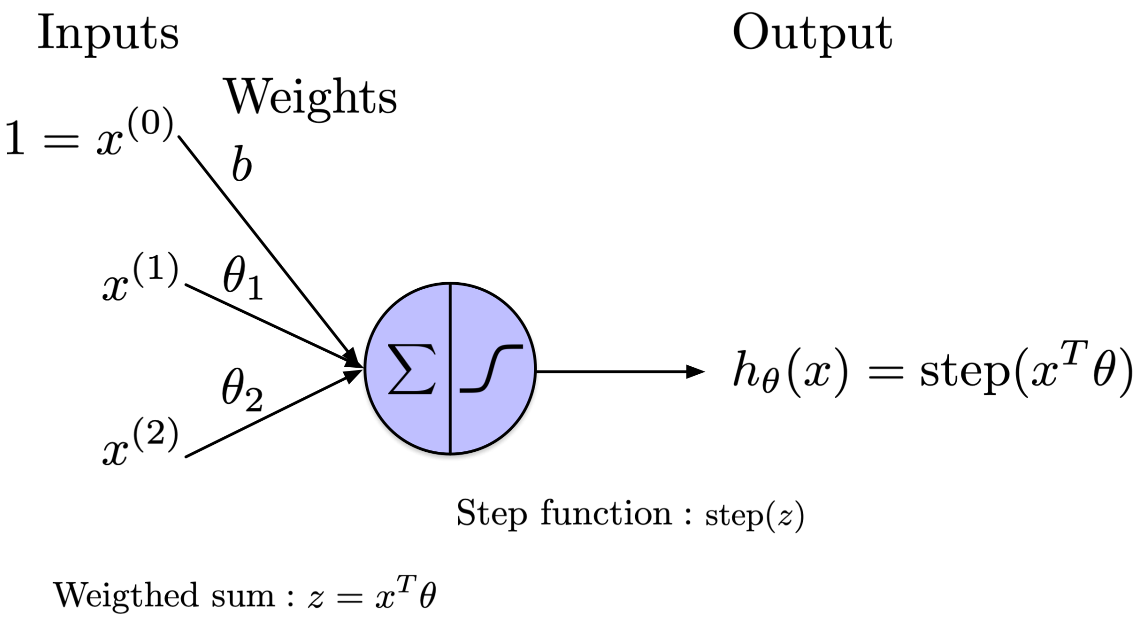


$\text{sign}(t)$ =

- 1, if $t > 0$
- 0, if $t = 0$
- -1, if $t < 0$

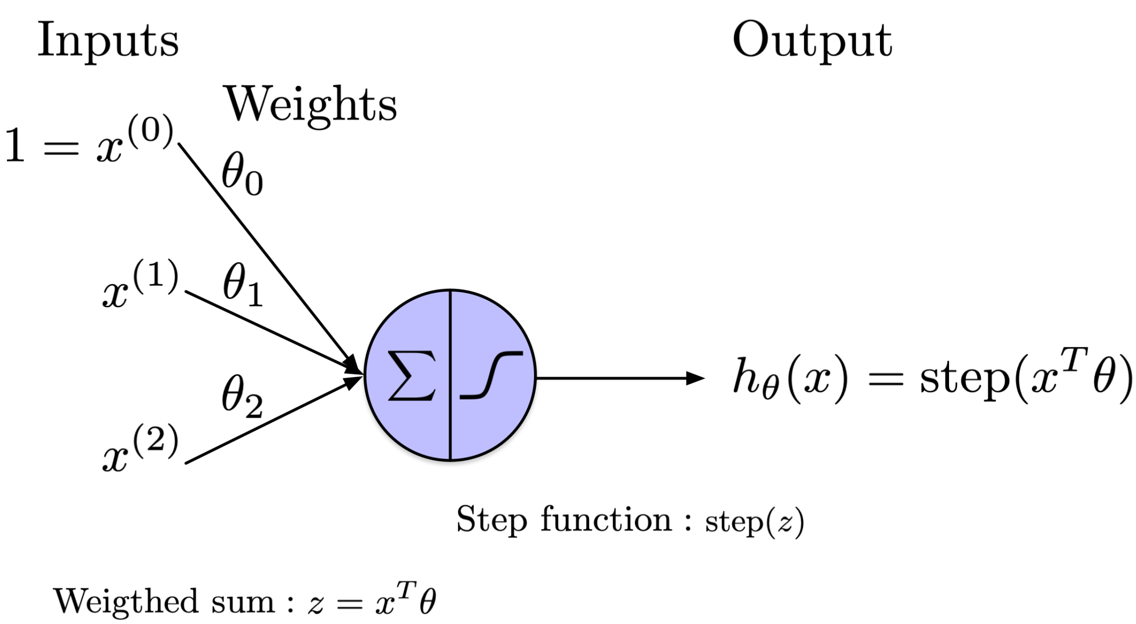
Common **step functions** include the **heavyside function** (0 if the input is negative and 1 otherwise) or the **sign** function (-1 if the input is negative, 0 if the input is zero, 1 otherwise).

Notation



Add an extra feature with a fixed value of 1 to the input. Associate it with weight $b = \theta_{0}$, where b is the bias/intercept term.

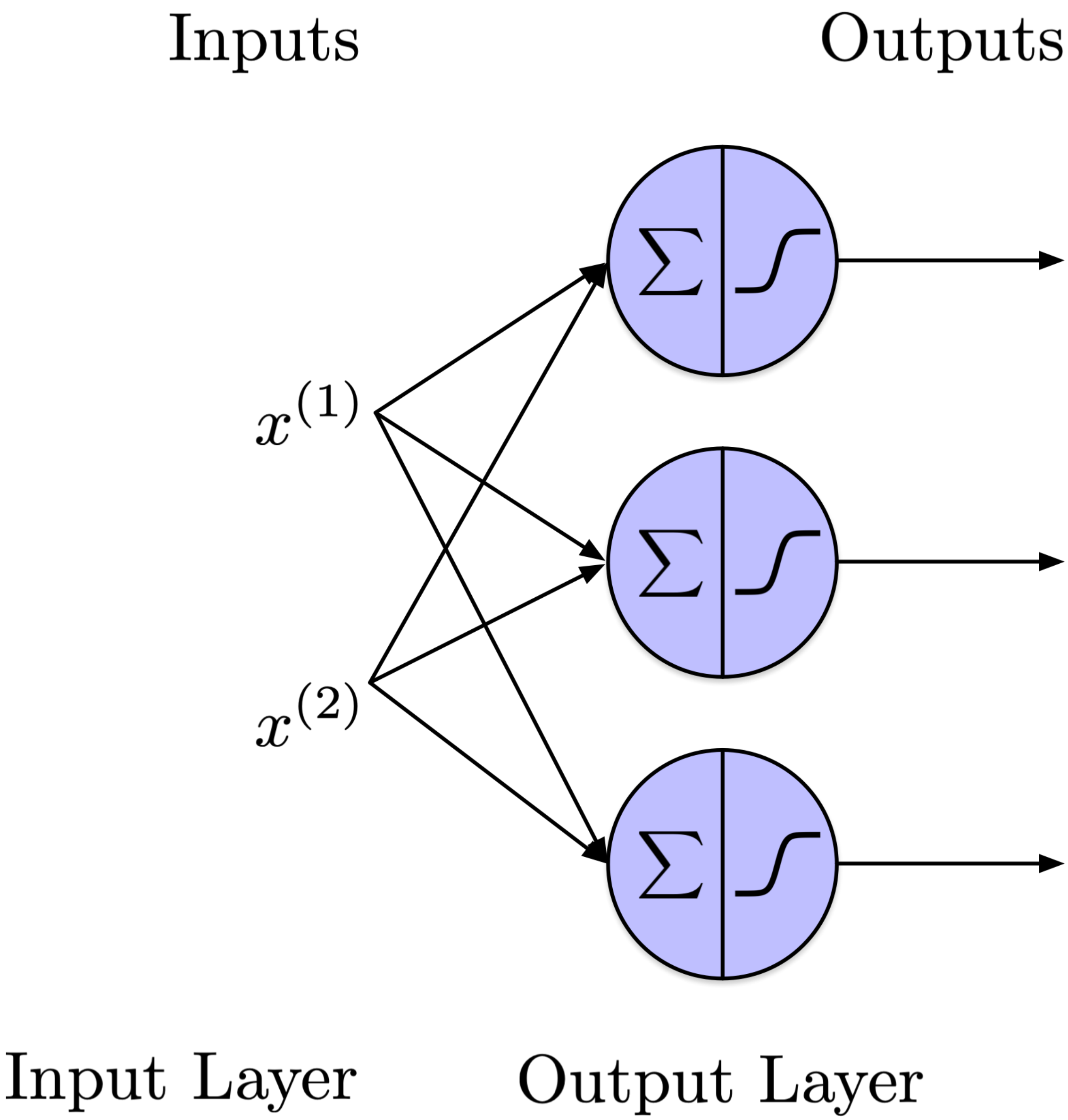
Notation



$\theta_{0} = b$ is the bias/intercept term.

The threshold logic unit is analogous to logistic regression, with the primary distinction being the substitution of the logistic (sigmoid) function with a step function. Similar to logistic regression, the perceptron is employed for classification tasks.

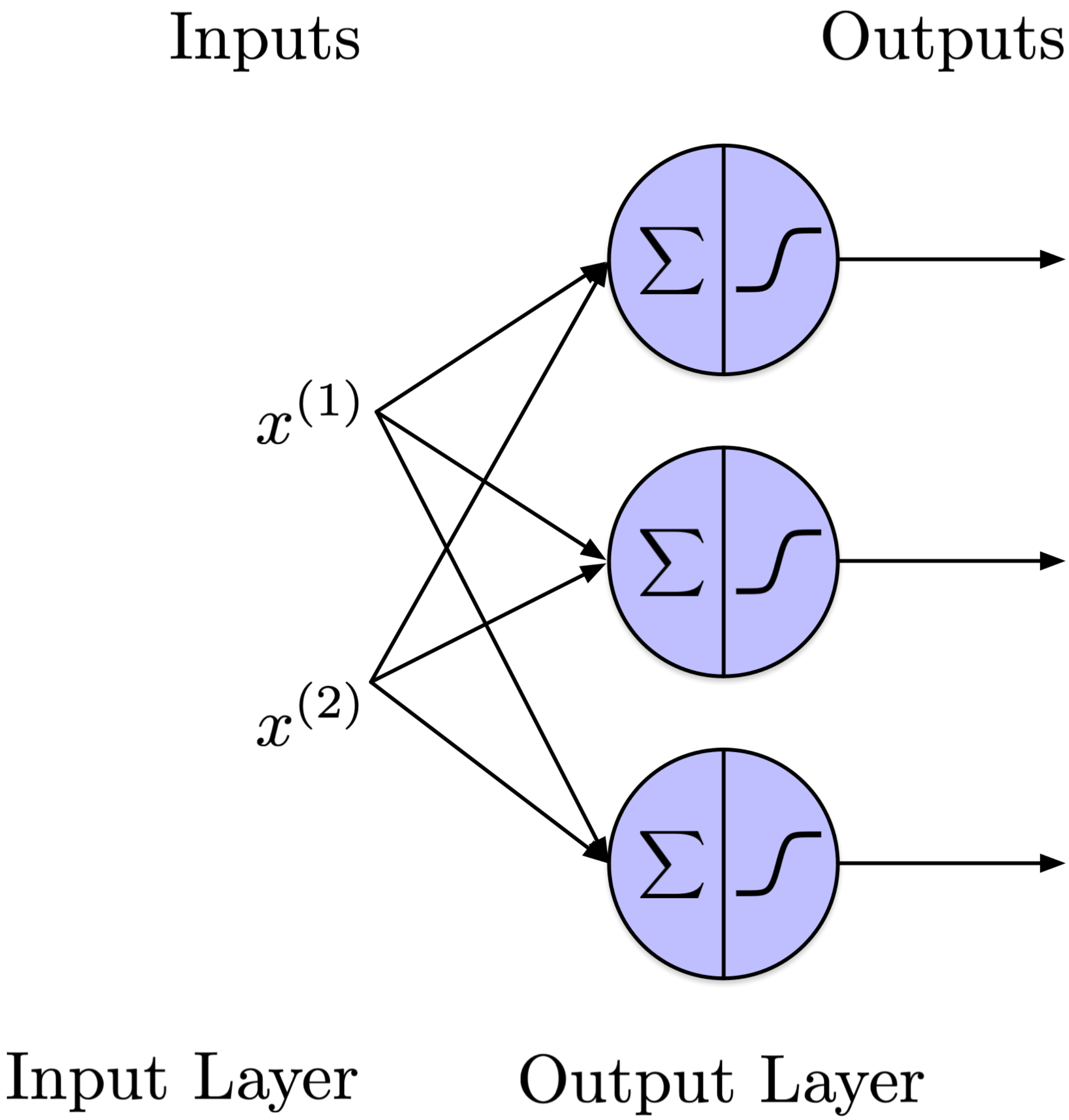
Perceptron



A **perceptron** consists of one or more **threshold logic units** arranged in a **single layer**, with each unit connected to all inputs. This configuration is referred to as **fully connected** or **dense**.

Since the threshold logic units in this single layer also generate the output, it is referred to as the **output layer**.

Perceptron



As this perceptron generates multiple outputs simultaneously, it performs **multiple binary predictions**, making it as a **multilabel classifier** (can also be used as multiclass classifier).

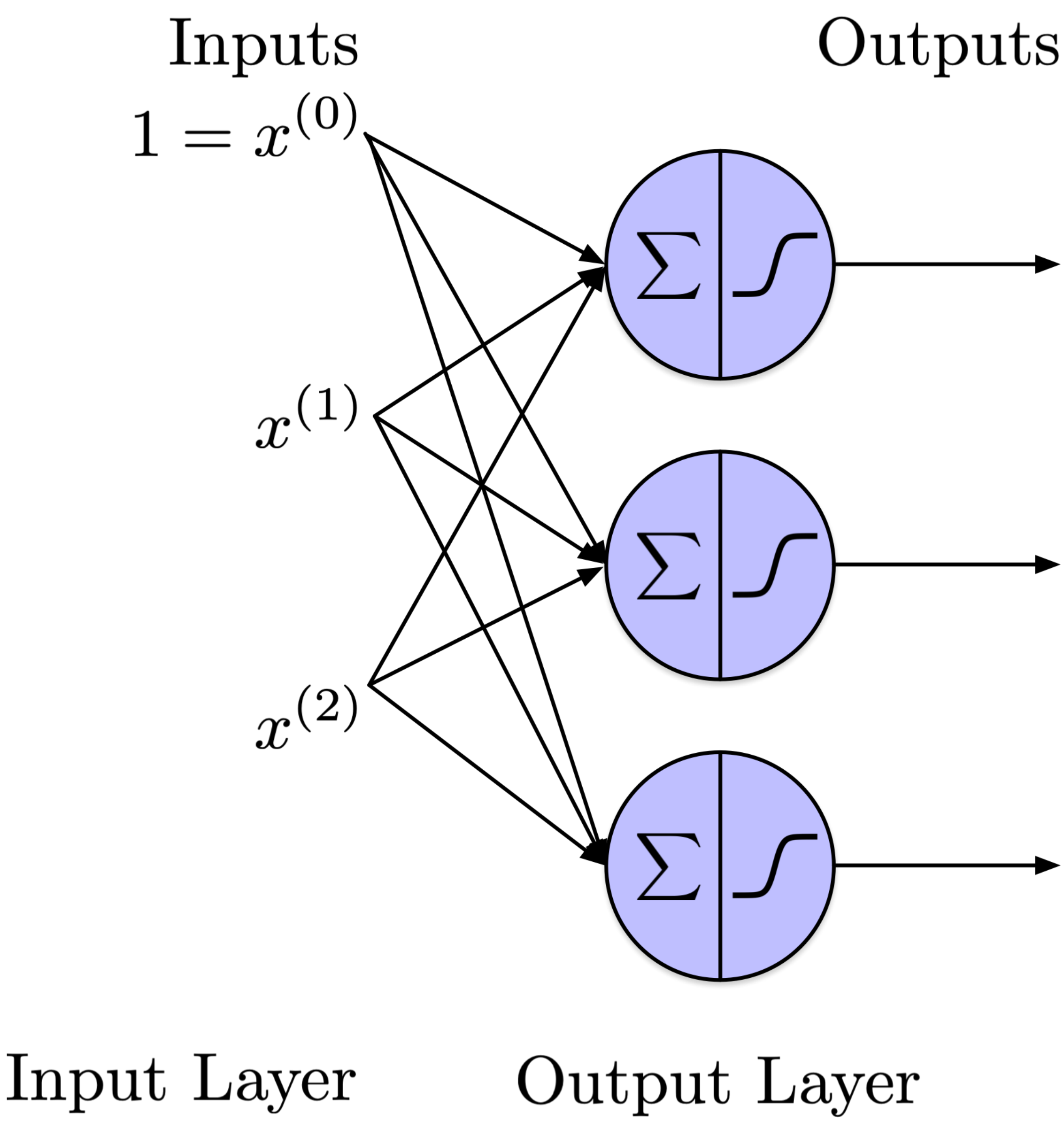
Classification tasks, can be further divided into **multilabel** and **multiclass** classification.

1. **Multiclass Classification:**
    - In multiclass classification, each instance is assigned to one and only one class out of a set of three or more possible classes. The classes are mutually exclusive, meaning that an instance cannot belong to more than one class at the same time.
    - **Example:** Classifying an image as either a cat, dog, or bird. Each image can only belong to one of these categories.

2. **Multilabel Classification:**
    - In multilabel classification, each instance can be associated with multiple classes simultaneously. The classes are not mutually exclusive, allowing for the possibility that an instance can belong to several classes at once.
    - **Example:** Tagging an image with multiple attributes such as “outdoor,” “sunset,” and “beach.” The image can simultaneously belong to all these labels.

The key difference lies in the relationship between classes: **multiclass classification deals with a single label per instance**, while **multilabel classification handles multiple labels for each instance**.

Notation



As before, introduce an additional feature with a value of 1 to the input. **Assign a bias b to each neuron.** Each incoming connection **implicitly** has an associated weight.

Notation

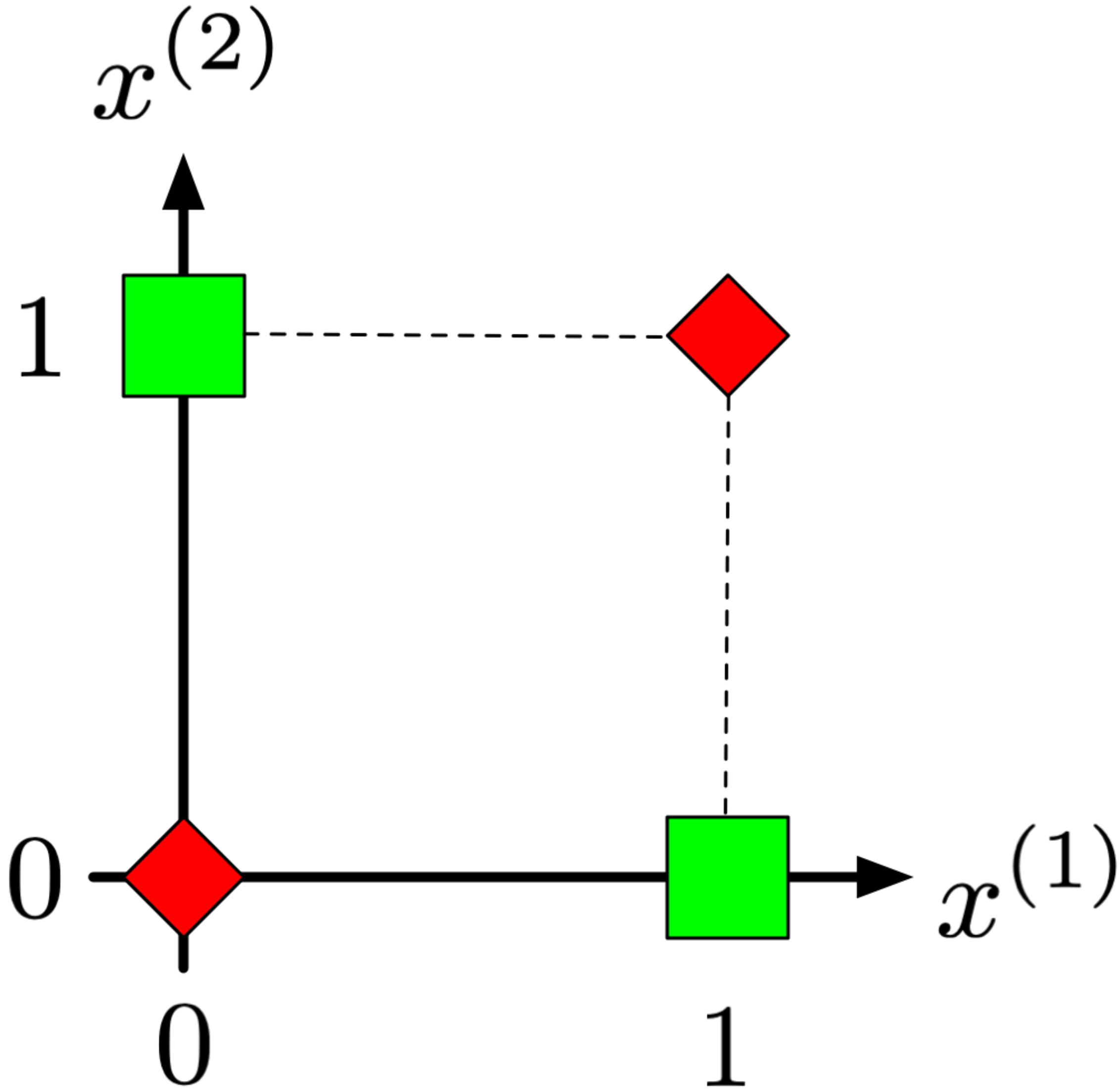
- X is the input **data matrix** where **each row corresponds to an example** and **each column represents one of the D features**.
- W is the **weight matrix**, structured with one **row per input (feature)** and **one column per neuron**.
- **Bias terms** can be represented separately; both approaches appear in the literature. Here, b is a vector with a **length equal to the number of neurons**.

With neural networks, the **parameters** of the model are often reffered to as w (vector) or W (matrix), rather than θ.

Discussion

- The algorithm to **train** the perceptron closely resembles stochastic gradient descent.
    - In the **interest of time** and to **avoid confusion**, we will skip this algorithm and focus on **multilayer perception** (MLP) and its training algorithm, **backpropagation**.

Historical Note and Justification

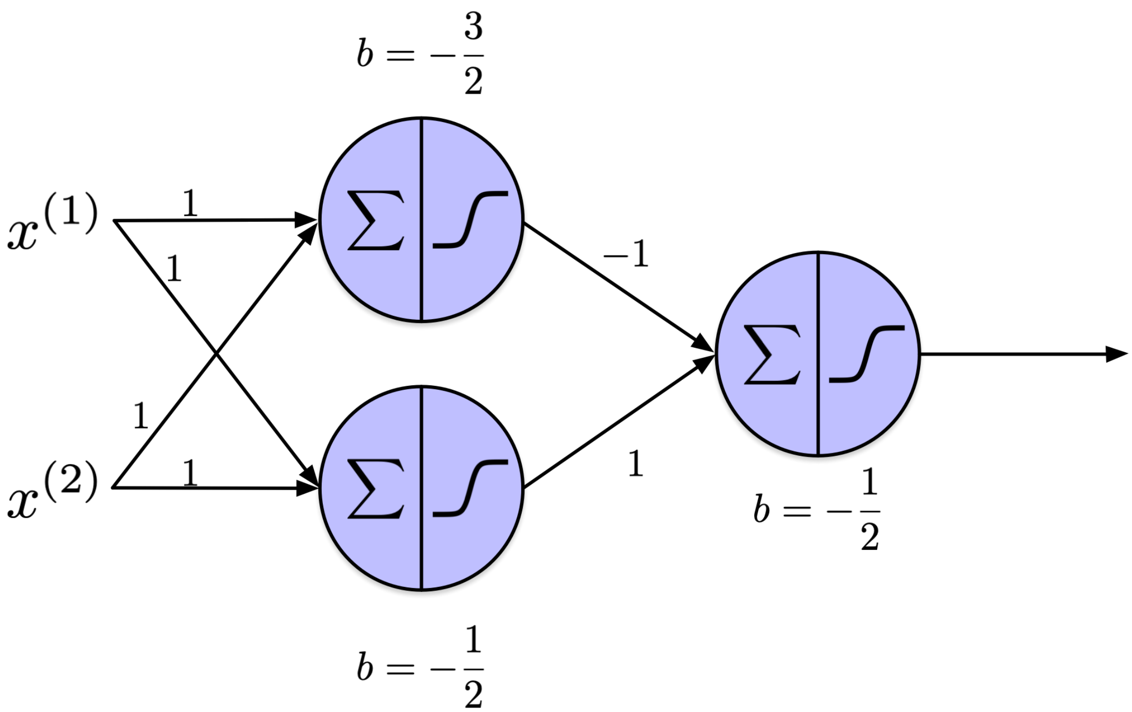


Minsky and Papert (1969) demonstrated the limitations of perceptrons, notably their inability to solve **exclusive OR** (XOR) classification problems: ${([0,1],\mathrm{true}), ([1,0],\mathrm{true}), ([0,0],\mathrm{false}), ([1,1],\mathrm{false})}$.

This limitation also applies to other linear classifiers, such as logistic regression.

Consequently, due to these limitations and a lack of practical applications, some researchers abandoned the perceptron.

Multilayer Perceptron



A **multilayer perceptron** (MLP) includes an input layer and one or more layers of threshold logic units. Layers that are neither input nor output are termed **hidden layers**.

XOR Classification Problem

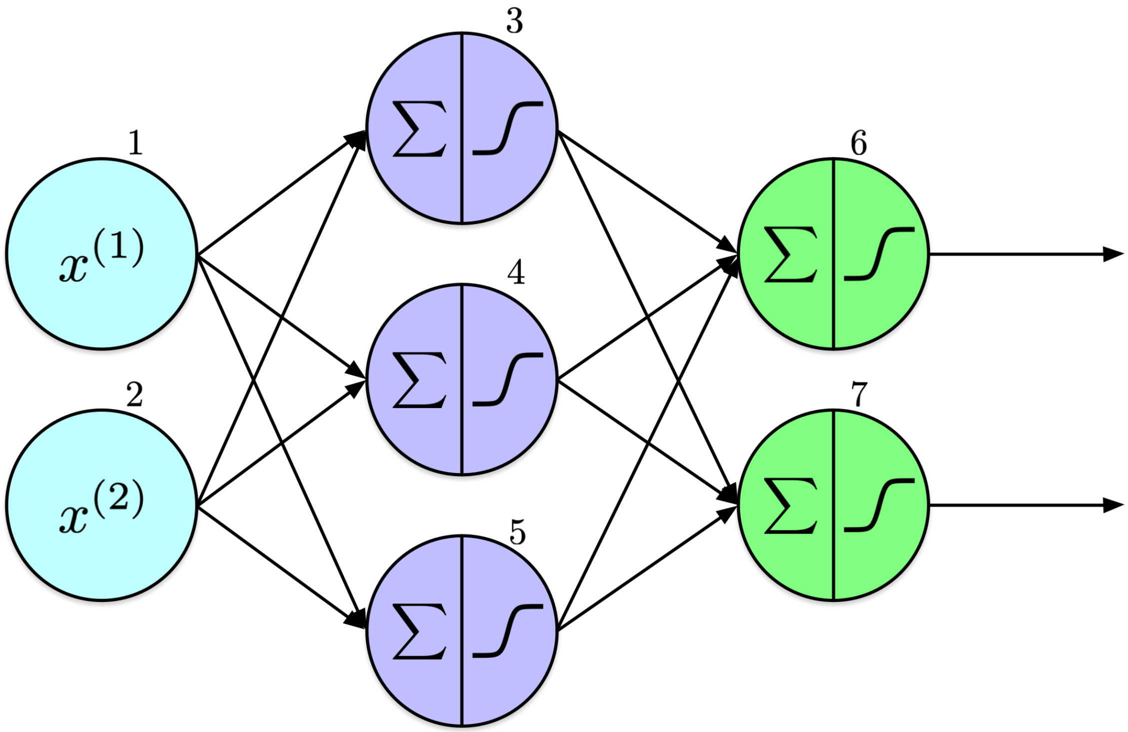
$x^{(1)}$	$x^{(2)}$	y	o_1	o_2	o_3
1	0	1	0	1	1
0	1	1	0	1	1
0	0	0	0	0	0
1	1	0	1	1	0

$x^{(1)}$ and $x^{(2)}$ are two attributes, y is the target, o_1, o_2, and $o_3 = h_\theta(x)$, are the output of the top left, bottom left, and right threshold units. Clearly $h_\theta(x) = y, \forall x \in X$. The challenge during Rosenblatt's time was the lack of algorithms to train multi-layer networks.

I developed an Excel spreadsheet to verify that the proposed multilayer perceptron effectively solves the XOR classification problem.

The step function used in the above model is the heavyside function.

Feedforward Neural Network (FNN)



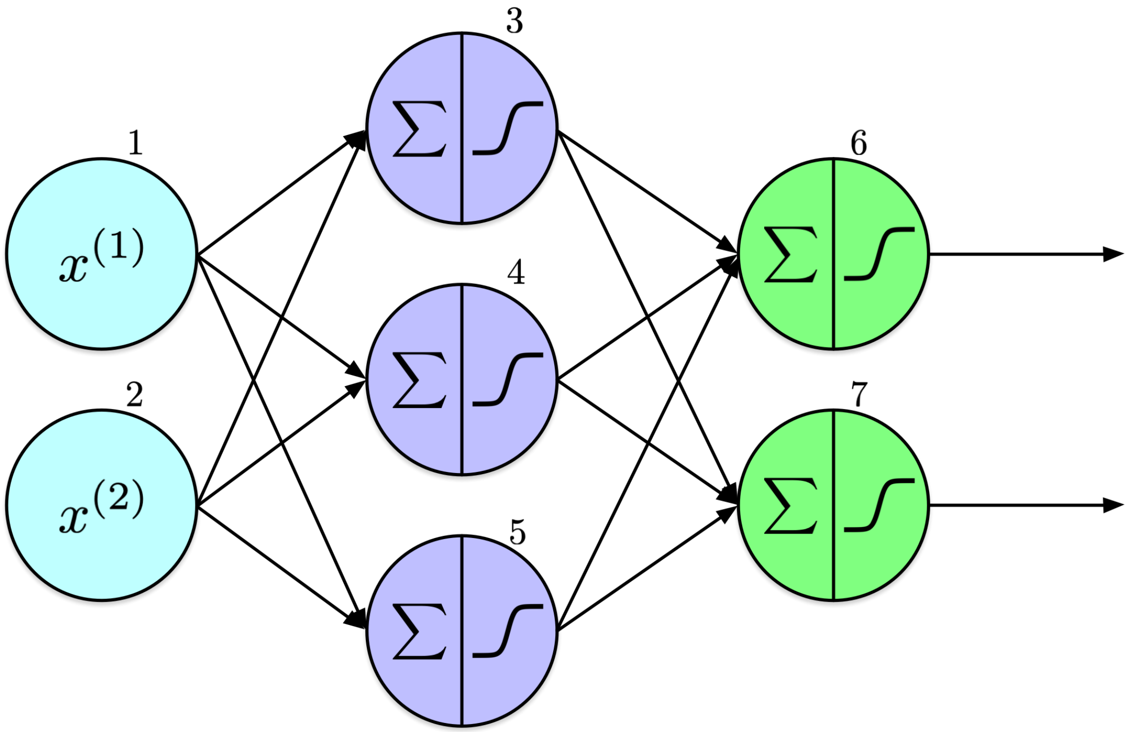
Information in this architecture flows unidirectionally—from left to right, moving from input to output. Consequently, it is termed a **feedforward neural network**.

The network consists of **three layers**: input, hidden, and output. The **input layer** contains two nodes, the **hidden layer** comprises three nodes, and the **output layer** has two nodes. Additional hidden layers and nodes per layer can be added, which will be discussed later.

It is often useful to include explicit input nodes that do not perform calculations, known as **input units** or **input neurons**. These nodes act as placeholders to introduce input features into the network, passing data directly to the next layer without transformation. In the network diagram, these are the light blue nodes on the left, labeled 1 and 2. Typically, **the number of input units corresponds to the number of features**.

For clarity, nodes are labeled to facilitate discussion of the weights between them, such as $w_{1,5}$ between nodes 1 and 5. Similarly, the output of a node is denoted by o_k, where k represents the node's label. For example, for $k=3$, the output would be o_3.

Forward Pass (Computation)



$o3 = \sigma(w_{13} x^{(1)}+ w_{23} x^{(2)} + b_3)$

$o4 = \sigma(w_{14} x^{(1)}+ w_{24} x^{(2)} + b_4)$

$o5 = \sigma(w_{15} x^{(1)}+ w_{25} x^{(2)} + b_5)$

$o6 = \sigma(w_{36} o_3 + w_{46} o_4 + w_{56} o_5 + b_6)$

$o7 = \sigma(w_{37} o_3 + w_{47} o_4 + w_{57} o_5 + b_7)$

First, it's important to **understand the information flow**: this network **computes** two outputs from its inputs.

To simplify the figure, I have opted not to display the bias terms, though they remain crucial components. Specifically, b_3 represents the bias term associated with node 3.

If bias terms were not significant, the training process would naturally reduce them to zero. Bias terms are essential as they enable the adjustment of the decision boundary, allowing the model to learn more complex patterns that weights alone cannot capture. By offering additional degrees of freedom, they also contribute to faster convergence during training.

Forward Pass (Computation)

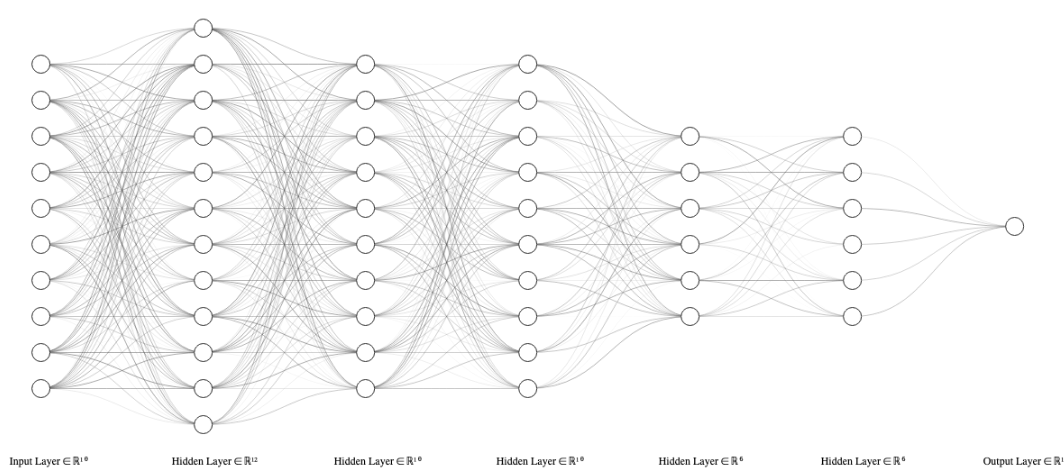
In [2]:
```
import numpy as np
```

```
# Sigmoid function

def sigma(x):
    return 1 / (1 + np.exp(-x))

# Input (two attributes) vector, one example of our trainig set

x1, x2 = (0.5, 0.9)

# Initializing the weights of layers 2 and 3 to random values

w13, w14, w15, w23, w24, w25 = np.random.uniform(low=-1, high=1, size=
w36, w46, w56, w37, w47, w57 = np.random.uniform(low=-1, high=1, size=

# Initializing all 5 bias terms to random values

b3, b4, b5, b6, b7 = np.random.uniform(low=-1, high=1, size=5)

o3 = sigma(w13 * x1 + w23 * x2 + b3)
o4 = sigma(w14 * x1 + w24 * x2 + b4)
o5 = sigma(w15 * x1 + w25 * x2 + b5)
o6 = sigma(w36 * o3 + w46 * o4 + w56 * o5 + b6)
o7 = sigma(w37 * o3 + w47 * o4 + w57 * o5 + b7)

(o6, o7)
```

```
(0.5027642045632127, 0.39398584263466113)
```

The example above illustrates the computation process with specific values. Before training a neural network, it is standard practice to initialize the weights and biases with random values. Gradient descent is then employed to iteratively adjust these parameters, aiming to minimize the loss function.

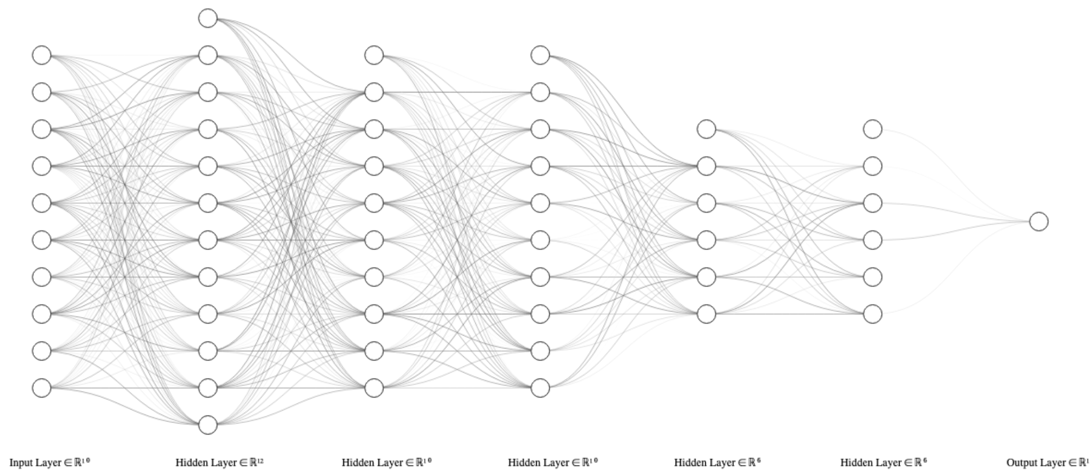
Forward Pass (Computatation)



The information flow remains consistent even in more **complex networks**. Networks with many layers are called **deep neural networks** (DNN).

Produced using **NN-SVG**, LeNail (2019).

Forward Pass (Computatation)



Same network with **bias terms shown**.

Produced using **NN-SVG**, LeNail (2019).

Activation Function

- As will be discussed later, the training algorithm, known as **backpropagation**, employs **gradient descent**, necessitating the calculation of the **partial derivatives of the loss function**.
- The **step function** in the multilayer perceptron had to be replaced, as it consists only of flat surfaces. **Gradient descent cannot progress on flat surfaces due to their zero derivative**.

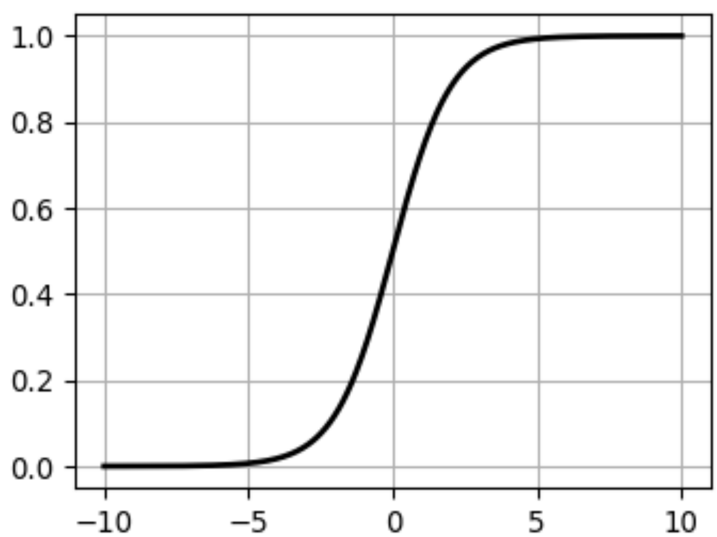
Activation Function

- **Nonlinear activation functions are paramount** because, without them, multiple layers in the network would only compute a linear function of the inputs.
- According to the **Universal Approximation Theorem**, sufficiently large deep networks with nonlinear activation functions can **approximate any**

continuous function. See Universal Approximation Theorem.

Sigmoid

In [3]:
```
import numpy as np
import matplotlib.pyplot as plt

# Sigmoid function
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

# Generate x values
x = np.linspace(-10, 10, 400)

# Compute y values for the sigmoid function
y = sigmoid(x)

plt.figure(figsize=(4,3))
plt.plot(x, y, color='black', linewidth=2)
plt.grid(True)
plt.show()
plt.show()
```

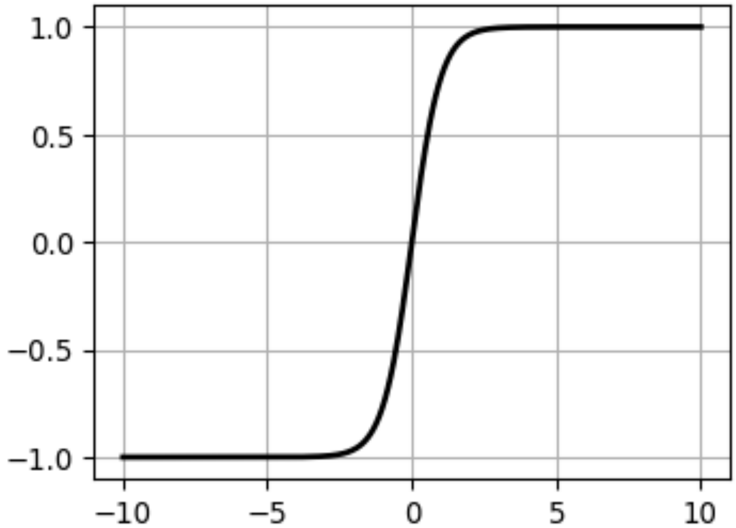


$$ \sigma(t) = \frac{1}{1 + e^{-t}} $$

Hyperbolic Tangent Function

In [4]:
```
# Compute y values for the hyperbolic tangent function

y = np.tanh(x)

plt.figure(figsize=(4,3))
plt.plot(x, y, color='black', linewidth=2)
```

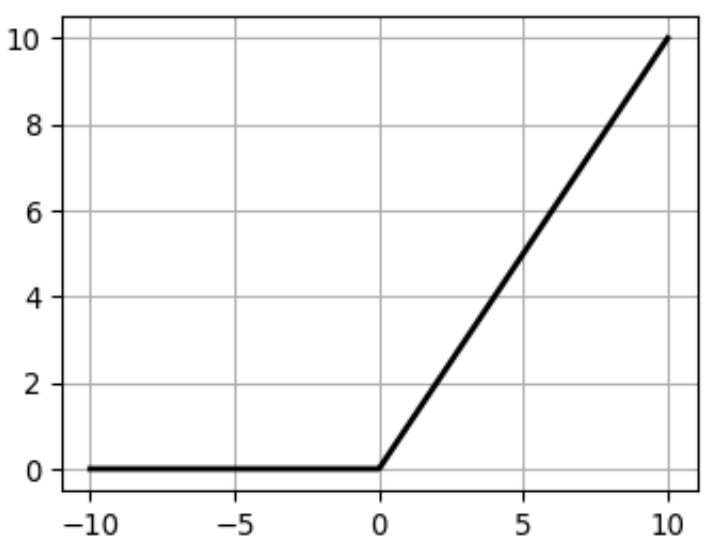
```
plt.grid(True)
plt.show()
```



Hyperbolic tangent ($\tanh(t) = 2 \sigma(2t) - 1$) is an S-shaped curve, similar to the sigmoid function, producing output values ranging from -1 to 1. According to Géron (2022), this range helps each layer's output to be approximately centered around 0 at the start of training, thereby **accelerating convergence**.

Rectified linear unit function (ReLU)

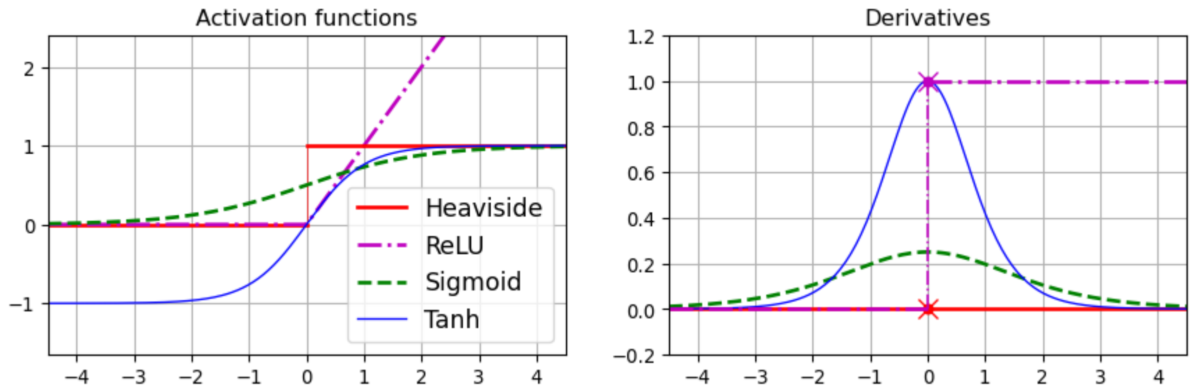
In [5]:
```
# Compute y values for the rectified linear unit function (ReLU) funct
y = np.maximum(0, x)

plt.figure(figsize=(4,3))
plt.plot(x, y, color='black', linewidth=2)
plt.grid(True)
plt.show()
```



Although the **ReLU function** ($\mathrm{ReLU}(t) = \max(0, t)$) is not differentiable at $t=0$ and has a derivative of 0 for $t<0$, it performs quite well in practice and is computationally efficient. Consequently, it has become the **default activation function**.

Common Activation Functions

In [6]:
```
from scipy.special import expit as sigmoid

def relu(z):
    return np.maximum(0, z)

def derivative(f, z, eps=0.000001):
    return (f(z + eps) - f(z - eps))/(2 * eps)

max_z = 4.5
z = np.linspace(-max_z, max_z, 200)

plt.figure(figsize=(11, 3.1))

plt.subplot(121)
plt.plot([-max_z, 0], [0, 0], "r-", linewidth=2, label="Heaviside")
plt.plot(z, relu(z), "m-.", linewidth=2, label="ReLU")
plt.plot([0, 0], [0, 1], "r-", linewidth=0.5)
plt.plot([0, max_z], [1, 1], "r-", linewidth=2)
plt.plot(z, sigmoid(z), "g--", linewidth=2, label="Sigmoid")
plt.plot(z, np.tanh(z), "b-", linewidth=1, label="Tanh")
plt.grid(True)
plt.title("Activation functions")
plt.axis([-max_z, max_z, -1.65, 2.4])
plt.gca().set_yticks([-1, 0, 1, 2])
plt.legend(loc="lower right", fontsize=13)

plt.subplot(122)
plt.plot(z, derivative(np.sign, z), "r-", linewidth=2, label="Heavisid
plt.plot(0, 0, "ro", markersize=5)
plt.plot(0, 0, "rx", markersize=10)
plt.plot(z, derivative(sigmoid, z), "g--", linewidth=2, label="Sigmoid
plt.plot(z, derivative(np.tanh, z), "b-", linewidth=1, label="Tanh")
plt.plot([-max_z, 0], [0, 0], "m-.", linewidth=2)
plt.plot([0, max_z], [1, 1], "m-.", linewidth=2)
plt.plot([0, 0], [0, 1], "m-.", linewidth=1.2)
plt.plot(0, 1, "mo", markersize=5)
plt.plot(0, 1, "mx", markersize=10)
plt.grid(True)
plt.title("Derivatives")
plt.axis([-max_z, max_z, -0.2, 1.2])

plt.show()
```



Géron (2022) – 10_neural_nets_with_keras.ipynb

Universal Approximation

Definition

The **Universal Approximation Theorem (UAT)** states that a feedforward neural network with a *single hidden layer* containing a *finite number of neurons* can **approximate any continuous function** on a compact subset of $\mathbb{R}^n$, given appropriate weights and activation functions.

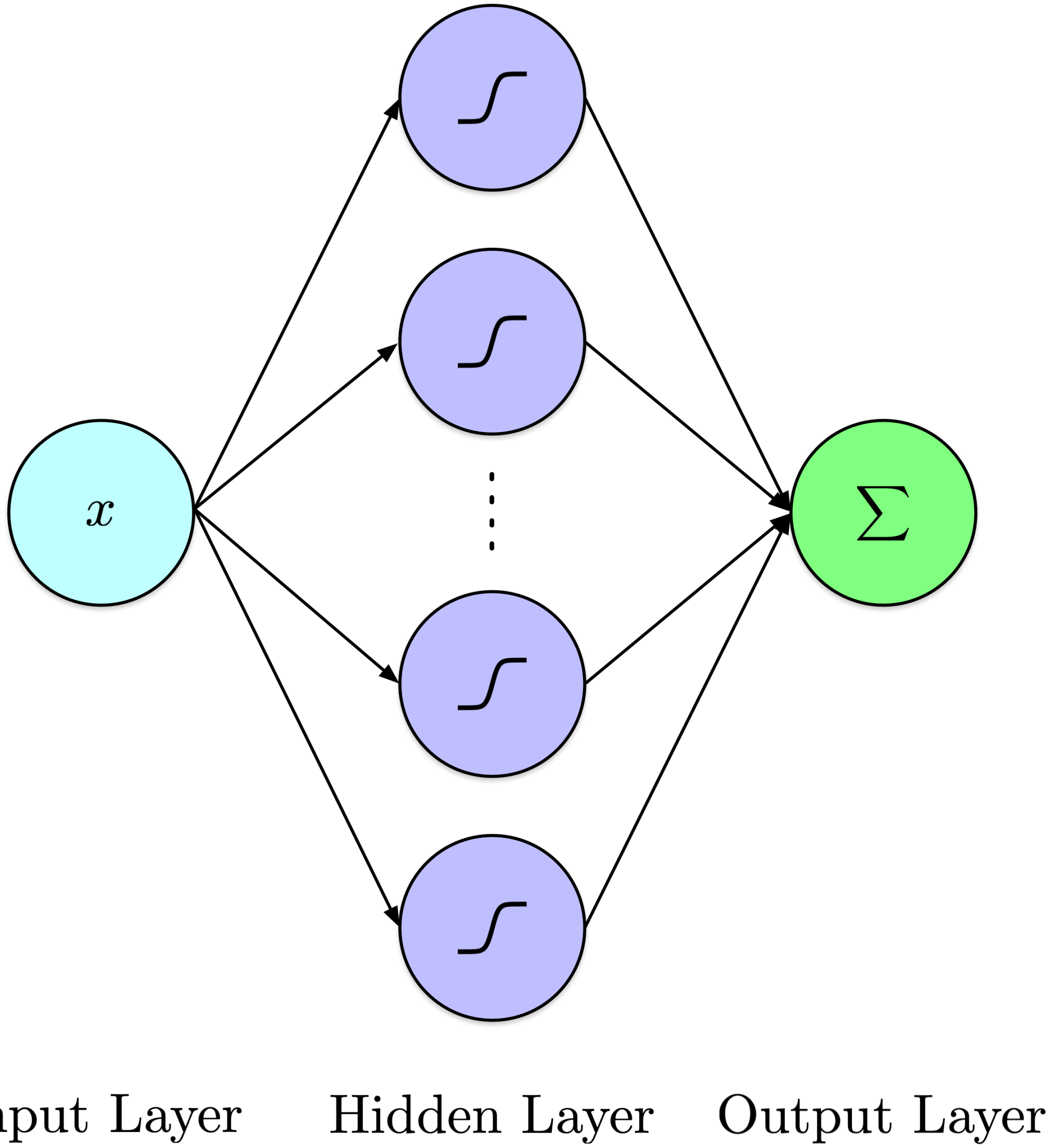
Cybenko (1989); Hornik, Stinchcombe, and White (1989)

In mathematical terms, a subset of $\mathbb{R}^n$ is considered **compact** if it is both **closed** and **bounded**.

- **Closed**: A set is closed if it contains all its boundary points. In other words, it includes its limit points or accumulation points.
- **Bounded**: A set is bounded if there exists a real number (M) such that the distance between any two points in the set is less than M.

In the context of the universal approximation theorem, compactness ensures that the function being approximated is defined on a finite and well-behaved region, which is crucial for the theoretical guarantees provided by the theorem.

Single Hidden Layer



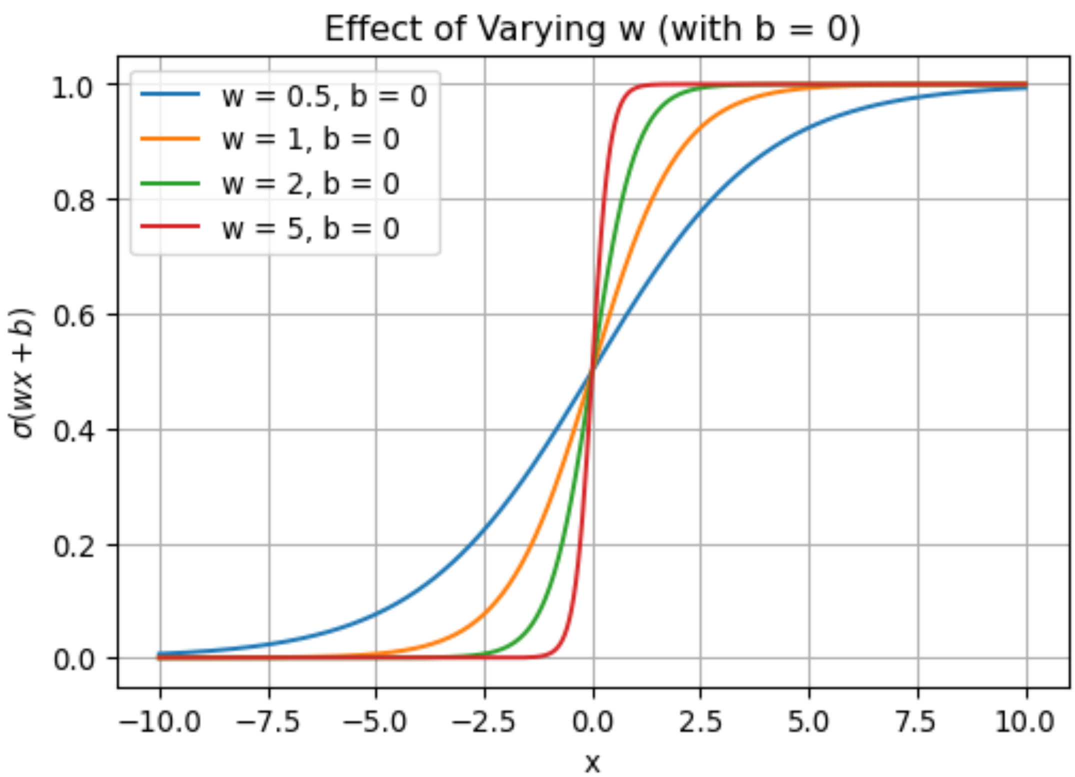
$$ y = \sum_{i=1}^N \alpha_i \sigma(w_{1,i} x + b_i) $$

Notation adapted to follow that of Cybenko (1989).

Effect of Varying w

In [7]:
```
def logistic(x, w, b):
    """Compute the logistic function with parameters w and b."""
    return 1 / (1 + np.exp(-(w * x + b)))

# Define a range for x values.
x = np.linspace(-10, 10, 400)

# Plot 1: Varying w (steepness) with b fixed at 0.
plt.figure(figsize=(6,4))
w_values = [0.5, 1, 2, 5]  # different steepness values
b = 0  # fixed bias
```

```
for w in w_values:
    plt.plot(x, logistic(x, w, b), label=f'w = {w}, b = {b}')
plt.title('Effect of Varying w (with b = 0)')
plt.xlabel('x')
plt.ylabel(r'$\sigma(wx+b)$')
plt.legend()
plt.grid(True)

plt.show()
```

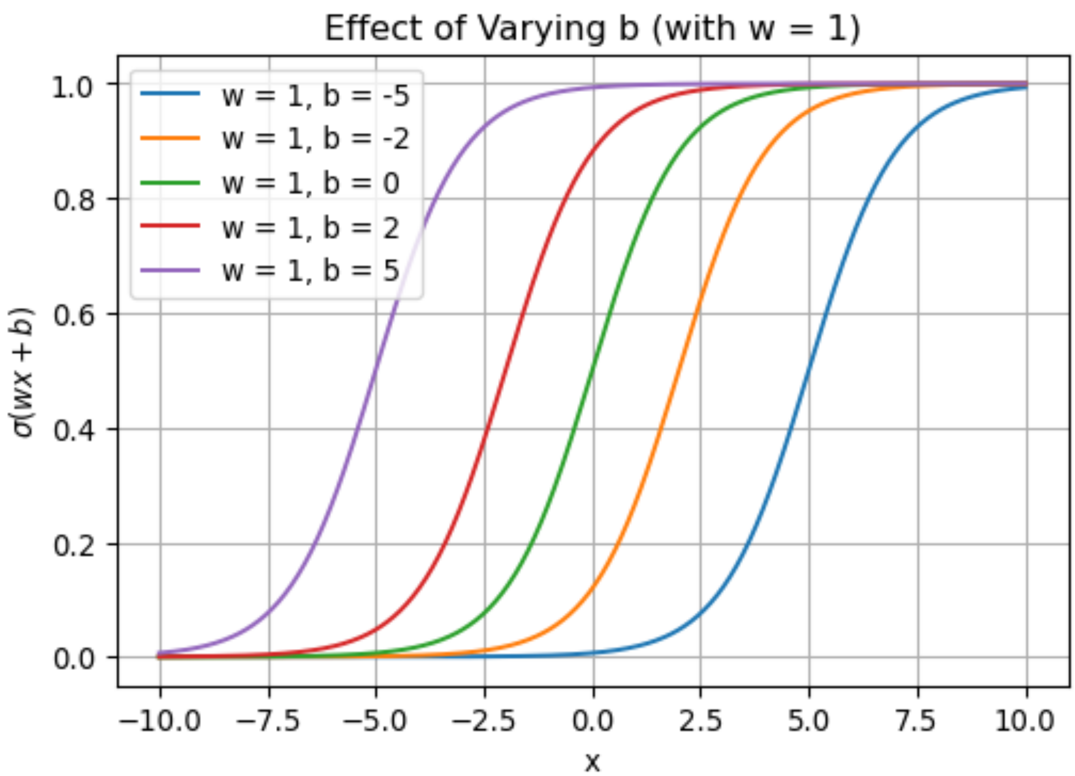


Sigmoid activation function: $\sigma(wx+b)$.

Effect of Varying b

In [8]:
```
# Plot 2: Varying b (horizontal shift) with w fixed at 1.
plt.figure(figsize=(6,4))
w = 1  # fixed steepness
b_values = [-5, -2, 0, 2, 5]  # different bias values

for b in b_values:
    plt.plot(x, logistic(x, w, b), label=f'w = {w}, b = {b}')
plt.title('Effect of Varying b (with w = 1)')
plt.xlabel('x')
plt.ylabel(r'$\sigma(wx+b)$')
plt.legend()
plt.grid(True)
```

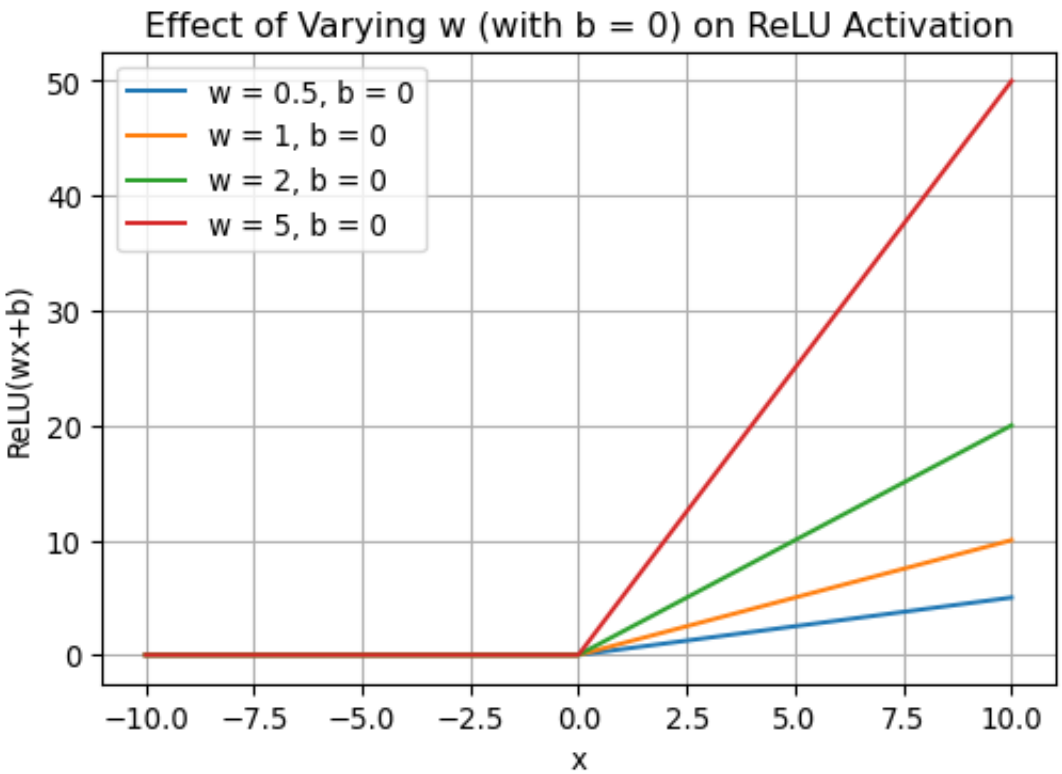
```
plt.show()
```



Sigmoid activation function: $\sigma(wx+b)$.

Effect of Varying w

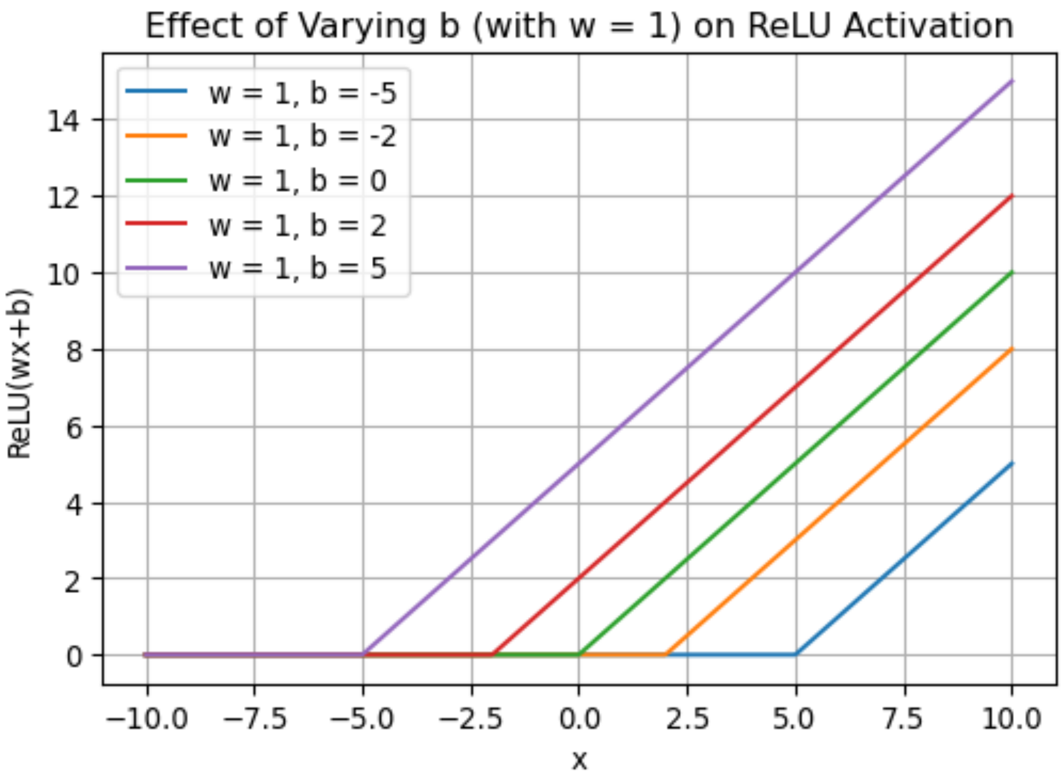
In [9]:
```
def relu(x, w, b):
    """Compute the ReLU activation with parameters w and b."""
    return np.maximum(0, w * x + b)

# Define a range for x values.
x = np.linspace(-10, 10, 400)

# Plot 1: Varying w (scaling) with b fixed at 0.
plt.figure(figsize=(6,4))
w_values = [0.5, 1, 2, 5]  # different scaling values
b = 0  # fixed bias

for w in w_values:
    plt.plot(x, relu(x, w, b), label=f'w = {w}, b = {b}')
plt.title('Effect of Varying w (with b = 0) on ReLU Activation')
plt.xlabel('x')
plt.ylabel('ReLU(wx+b)')
plt.legend()
plt.grid(True)

plt.show()
```



ReLU activation function: `np.maximum(0, w * x + b)`.

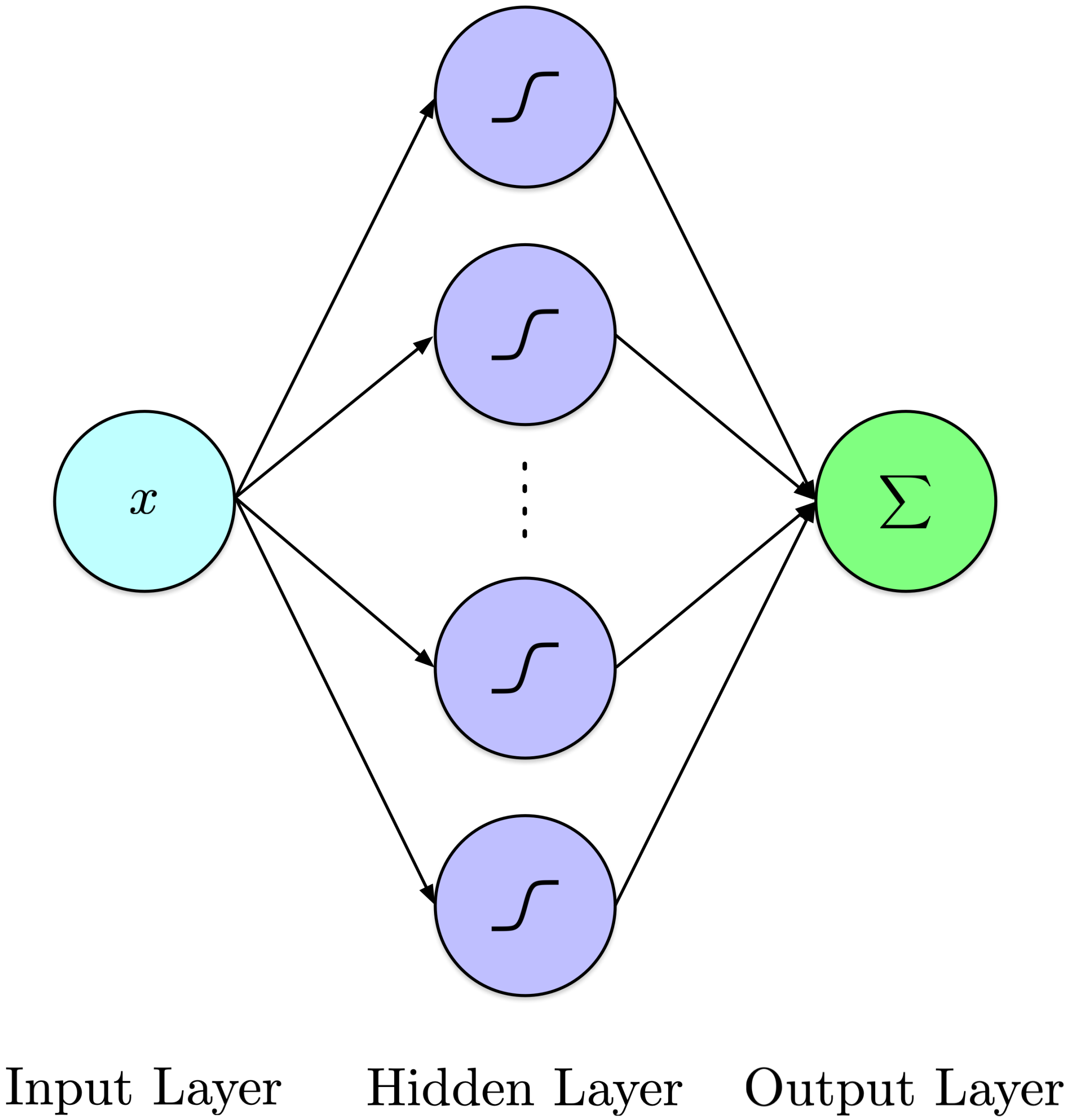
Effect of Varying b

In [10]:
```
# Plot 2: Varying b (horizontal shift) with w fixed at 1.
plt.figure(figsize=(6,4))
w = 1  # fixed scaling
b_values = [-5, -2, 0, 2, 5]  # different bias values

for b in b_values:
    plt.plot(x, relu(x, w, b), label=f'w = {w}, b = {b}')
plt.title('Effect of Varying b (with w = 1) on ReLU Activation')
plt.xlabel('x')
plt.ylabel('ReLU(wx+b)')
plt.legend()
plt.grid(True)

plt.show()
```



ReLU activation function: `np.maximum(0, w * x + b)`.

Single Hidden Layer



$$ y = \sum_{i=1}^N \alpha_i \sigma(w_{1,i} x + b_i) $$

See also: Chapter 4: A visual proof that neural nets can compute any function, Neural Networks and Deep Learning by Michael Nielsen.

Demonstration with Code

In [11]:
```
# Defining the function to be approximated

def f(x):
  return 2 * x**3 + 4 * x**2 - 5 * x + 1

# Generating a dataset, x in [-4,2), f(x) as above

X = 6 * np.random.rand(1000, 1) - 4
```

```
y = f(X).flatten()
```

Increasing the Number of Neurons

In [12]:

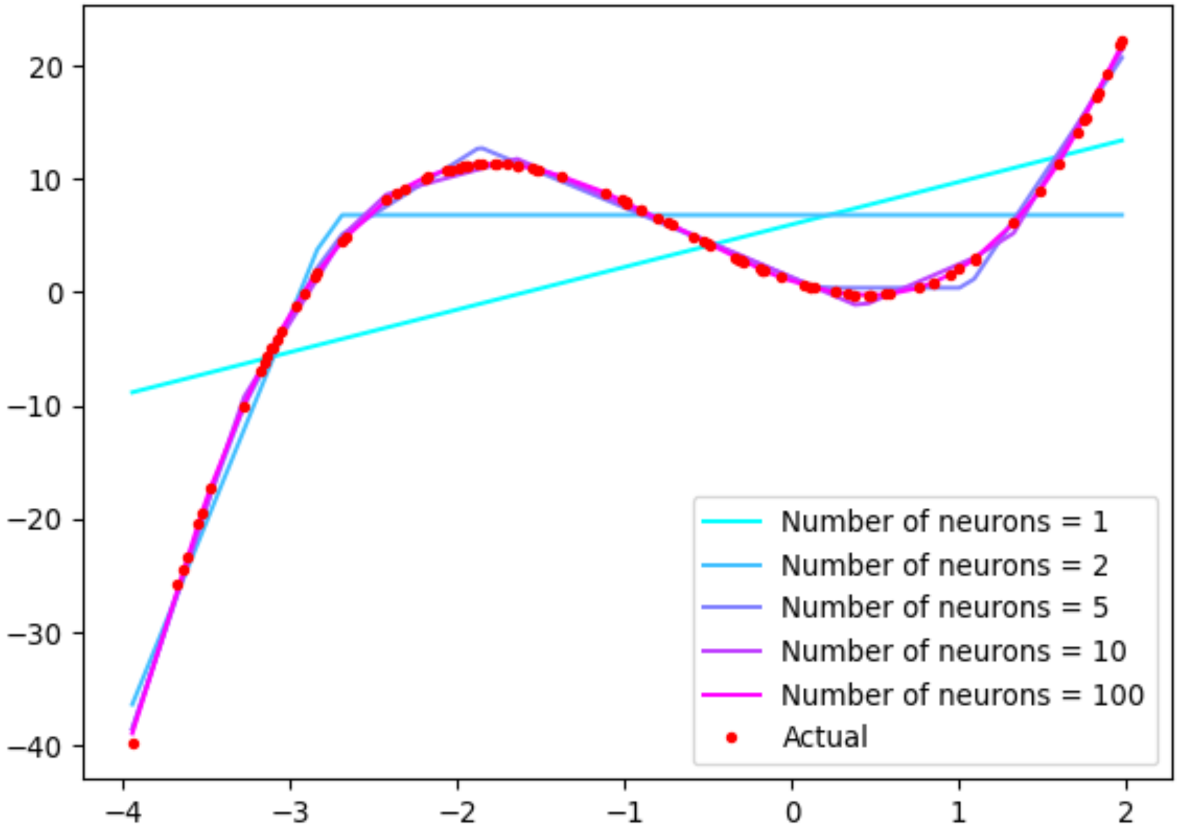
```
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import train_test_split

X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=

models = []

sizes = [1, 2, 5, 10, 100]

for i, n in enumerate(sizes):

  models.append(MLPRegressor(hidden_layer_sizes=[n], max_iter=5000, ra

  models[i].fit(X_train, y_train)
```

MLPRegressor is a multi-layer perceptron regressor from sklearn. Its default activation function is `relu`.

Increasing the Number of Neurons

In [13]:

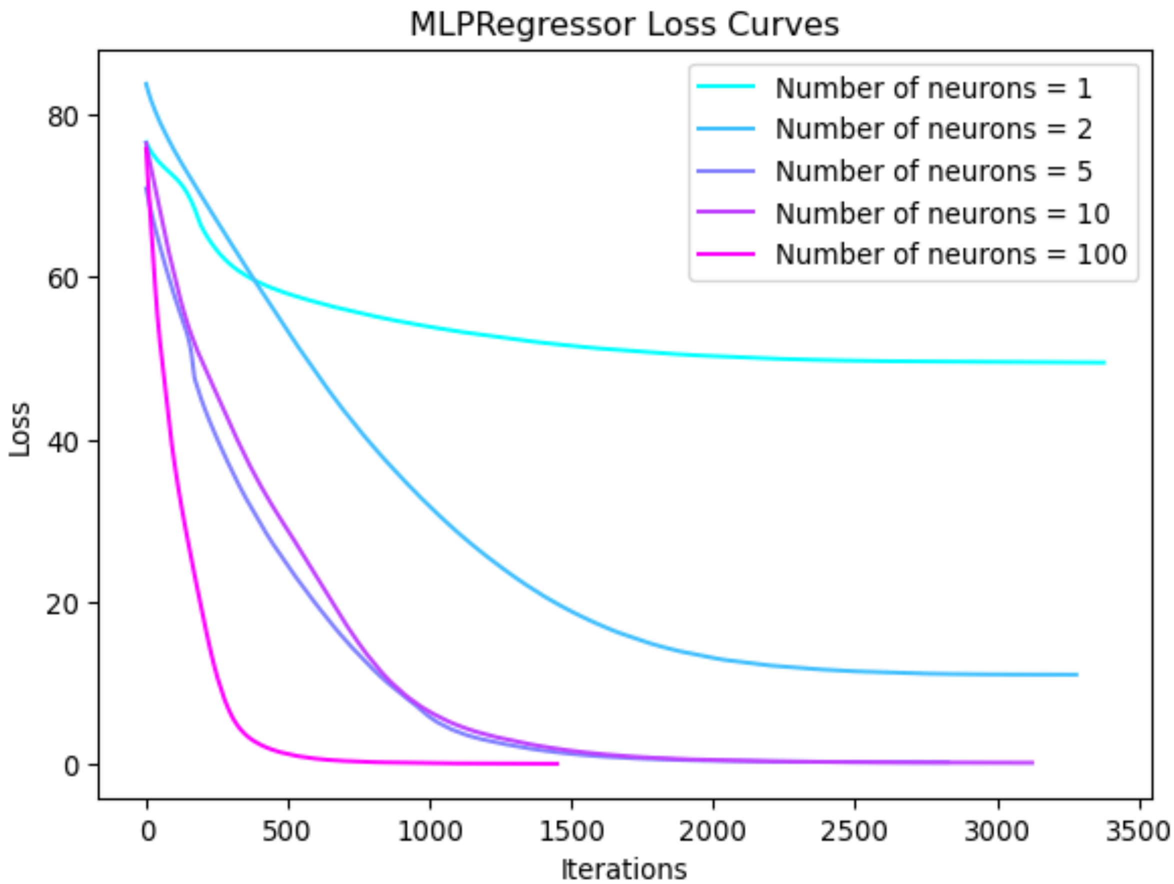
```
# Create a colormap
colors = plt.colormaps['cool'].resampled(len(sizes))

X_valid = np.sort(X_valid,axis=0)

for i, n in enumerate(sizes):

  y_pred = models[i].predict(X_valid)

  plt.plot(X_valid, y_pred, "-", color=colors(i), label="Number of neu

y_true = f(X_valid)
plt.plot(X_valid, y_true, "r.", label='Actual')

plt.legend()
plt.show()
```



In the example above, I retained only 10% of the data as the test set because the function being approximated is straightforward and noise-free. This decision was made to ensure that the true curve does not overshadow the other results.

Increasing the Number of Neurons

In [14]:
```
for i, n in enumerate(sizes):

  plt.plot(models[i].loss_curve_, "-", color=colors(i), label="Number

plt.title('MLPRegressor Loss Curves')
plt.xlabel('Iterations')
plt.ylabel('Loss')

plt.legend()
plt.show()
```



As expected, increasing neuron count reduces loss.

Universal Approximation

https://youtu.be/CqOfi41LfDw

This video effectively conveys the underlying intuition of the universal approximation theorem. (18m 53s)

The video effectively elucidates key concepts (terminology) in neural networks, including nodes, layers, weights, and activation functions. It demonstrates the process of summing activation outputs from a preceding layer, akin to the aggregation of curves. Additionally, the video illustrates how scaling an output by a weight not only alters the amplitude of a curve but also inverts its orientation when the weight is negative. Moreover, it clearly depicts the function of bias terms in vertically shifting the curve, contingent on the sign of the bias.

Let’s Code

Frameworks

PyTorch and TensorFlow are the leading platforms for deep learning.

- PyTorch has gained considerable traction in the **research community**. Initially developed by **Meta AI**, it is now part of the Linux Foundation.
- TensorFlow, created by **Google**, is widely adopted in **industry** for deploying models in production environments.

Keras

Keras is a high-level API designed to build, train, evaluate, and execute models across various backends, including PyTorch, TensorFlow, and JAX, Google's high-performance platform.

Keras is powerful enough for most projects.

As highlighted in previous Quotes of the Day, François Chollet, a Google engineer, is the originator and one of the primary developers of the Keras project.

Fashion-MNIST dataset

"Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of **60,000 examples** and a test set of **10,000 examples**. Each example is a **28x28 grayscale image**, associated with a label from **10 classes**."

Attribution: Géron (2022) – 10_neural_nets_with_keras.ipynb

Loading

In [15]:
```
import tensorflow as tf

fashion_mnist = tf.keras.datasets.fashion_mnist.load_data()

(X_train_full, y_train_full), (X_test, y_test) = fashion_mnist

X_train, y_train = X_train_full[:-5000], y_train_full[:-5000]
X_valid, y_valid = X_train_full[-5000:], y_train_full[-5000:]
```

Setting aside 5000 examples as a validation set.

Exploration

In [16]:
```
X_train.shape
```

```
(55000, 28, 28)
```

...

In [17]:
```
X_train.dtype
```

```
dtype('uint8')
```

...

Transforming the pixel intensities from integers in the range 0 to 255 to floats in the range 0 to 1.

In [18]:
```
X_train, X_valid, X_test = X_train / 255., X_valid / 255., X_test / 25
```

What are these Images Anyway?

In [19]:
```
plt.figure(figsize=(2, 2))
plt.imshow(X_train[0], cmap="binary")
plt.axis('off')
plt.show()
```

...

In [20]:
```
y_train
```

```
array([9, 0, 0, ..., 9, 0, 2], dtype=uint8)
```

...

Since the labels are integers, 0 to 9. Class names will become handy.

In [21]:
```
class_names = ["T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
               "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"]
```

First 40 Images

In [22]:
```
n_rows = 4
n_cols = 10
plt.figure(figsize=(n_cols * 1.2, n_rows * 1.2))
for row in range(n_rows):
    for col in range(n_cols):
        index = n_cols * row + col
        plt.subplot(n_rows, n_cols, index + 1)
        plt.imshow(X_train[index], cmap="binary", interpolation="neare
        plt.axis('off')
        plt.title(class_names[y_train[index]])
plt.subplots_adjust(wspace=0.2, hspace=0.5)
plt.show()
```

Creating a Model

In [23]:
```
tf.random.set_seed(42)

model = tf.keras.Sequential()

model.add(tf.keras.layers.InputLayer(shape=[28, 28]))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(300, activation="relu"))
model.add(tf.keras.layers.Dense(100, activation="relu"))
model.add(tf.keras.layers.Dense(10, activation="softmax"))
```

`model.summary()`

In [24]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	
flatten (Flatten)	(None, 784)	
dense (Dense)	(None, 300)	
dense_1 (Dense)	(None, 100)	
dense_2 (Dense)	(None, 10)	

Total params: 266,610 (1.02 MB)
Trainable params: 266,610 (1.02 MB)
Non-trainable params: 0 (0.00 B)

As observed, `dense_3` has $235,500$ parameters, while $784 \times 300 = 235,200$.

Could you explain the origin of the additional parameters?

Similarly, `dense_3` has $30,100$ parameters, while $300 \times 100 = 30,000$.

Can you explain why?

Creating a Model (Alternative)

In [25]:
```
# extra code – clear the session to reset the name counters
tf.keras.backend.clear_session()
tf.random.set_seed(42)
```

In [26]:
```
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=[28, 28]),
    tf.keras.layers.Dense(300, activation="relu"),
    tf.keras.layers.Dense(100, activation="relu"),
    tf.keras.layers.Dense(10, activation="softmax")
])
```

```
/Users/turcotte/opt/micromamba/envs/ml4bio/lib/python3.10/site-package
s/keras/src/layers/reshaping/flatten.py:37: UserWarning:

Do not pass an `input_shape`/`input_dim` argument to a layer. When usin
g Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
```

`model.summary()`

In [27]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	
flatten (Flatten)	(None, 784)	
dense (Dense)	(None, 300)	
dense_1 (Dense)	(None, 100)	
dense_2 (Dense)	(None, 10)	

Total params: 266,610 (1.02 MB)
Trainable params: 266,610 (1.02 MB)
Non-trainable params: 0 (0.00 B)

Compiling the Model

In [28]:
```
model.compile(loss="sparse_categorical_crossentropy",
              optimizer="sgd",
              metrics=["accuracy"])
```

`sparse_categorical_crossentropy` is the appropriate function for a multiclass classification problem (more later).

The method `compile` allows to set the loss function, as well as other parameters. Keras then prepares the model for training.

Training the Model

In [29]:
```
history = model.fit(X_train, y_train, epochs=30,
                    validation_data=(X_valid, y_valid))
```

```
Epoch 1/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 3:28 122ms/step - accuracy: 0.0625 - los
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s/step - accuracy: 0.6089 - loss: 1.2473▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━ 0s 764us/step - accuracy: 0.6169 - loss: 1.2198▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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oss: 1.1709▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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cy: 0.6374 - loss: 1.1497▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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s/step - accuracy: 0.6433 - loss: 1.1296▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.6537 - loss: 1.0944▯▯▯
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oss: 1.0786▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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cy: 0.6628 - loss: 1.0634▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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s/step - accuracy: 0.6670 - loss: 1.0491▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━ 0s 765us/step - accuracy: 0.6708 - loss: 1.0360▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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oss: 1.0114▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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cy: 0.6812 - loss: 1.0006▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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s/step - accuracy: 0.6815 - loss: 0.9996 - val_accuracy: 0.8278 - val_l
oss: 0.5071
Epoch 2/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.8750 - loss:
0.4716▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8374 - loss: 0.4954□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8276 - loss: 0.5139□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 776us/step - accuracy: 0.8238 - loss: 0.5212□□□□□□□□□□□□□□□□□□□□□□
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329/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 768us/step - accuracy: 0.8224 - loss:
0.5231□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8221 - loss: 0.5231□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8219 - loss: 0.5226□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 765us/step - accuracy: 0.8219 - loss: 0.5219□□□□□□□□□□□□□□□□□□□□□□
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661/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 762us/step - accuracy: 0.8224 - loss:
0.5202□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8227 - loss: 0.5194□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8231 - loss: 0.5186□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 758us/step - accuracy: 0.8234 - loss: 0.5177□□□□□□□□□□□□□□□□□□□□□□
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997/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8241 - loss:
0.5157□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8245 - loss: 0.5147□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8248 - loss: 0.5137□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 758us/step - accuracy: 0.8251 - loss: 0.5127□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8254 - loss: 0.5119□□□□□□□□
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329/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8257 - loss:
0.5111□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8260 - loss: 0.5102□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8263 - loss: 0.5094□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 758us/step - accuracy: 0.8265 - loss: 0.5085□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8268 - loss: 0.5077□□□□□□□□
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666/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 756us/step - accuracy: 0.8271 - loss:
0.5069▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8272 - loss: 0.5063 - val_accuracy: 0.8366 - val_loss: 0.4575
Epoch 3/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 12ms/step - accuracy: 0.9062 - loss:
0.4339▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯  67/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 766us/step - accuracy:
0.8570 - loss: 0.4280▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8486 - loss: 0.4472▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 1s 759us/step - accuracy: 0.8450 - loss: 0.4550▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 1s 759us/step - accuracy: 0.8438 - loss: 0.4572▯▯▯▯▯▯▯▯
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334/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 757us/step - accuracy: 0.8429 - loss:
0.4585▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8423 - loss: 0.4594▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8421 - loss: 0.4597▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 752us/step - accuracy: 0.8420 - loss: 0.4597▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 604/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 751us/step - accuracy: 0.8421 - loss: 0.4595▯▯▯▯▯▯▯▯
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671/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 751us/step - accuracy: 0.8422 - loss:
0.4592▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯ 740/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 749us/step - accuracy:
0.8424 - loss: 0.4589▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 809/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 747us/ste
p - accuracy: 0.8425 - loss: 0.4587▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 746us/step - accuracy: 0.8427 - loss: 0.4584▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.8428 - loss: 0.4579▯▯▯▯▯▯▯▯
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013/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.8430 - loss:
0.4574▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1079/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 746us/step - accuracy:
0.8432 - loss: 0.4569▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1147/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 746us/ste
p - accuracy: 0.8434 - loss: 0.4563▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 746us/step - accuracy: 0.8435 - loss: 0.4558▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1282/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 746us/step - accuracy: 0.8437 - loss: 0.4554▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1
347/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 747us/step - accuracy: 0.8438 - loss:
0.4549▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1413/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 748us/step - accuracy:
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0.8440 - loss: 0.4545
1478/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 749us/step - accuracy: 0.8441 - loss: 0.4540
1544/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 750us/step - accuracy: 0.8443 - loss: 0.4535
1611/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 750us/step - accuracy: 0.8444 - loss: 0.4531
1678/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 750us/step - accuracy: 0.8445 - loss: 0.4527
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 804us/step - accuracy: 0.8446 - loss: 0.4524 - val_accuracy: 0.8434 - val_loss: 0.4348
Epoch 4/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9062 - loss: 0.4343
  67/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 762us/step - accuracy: 0.8698 - loss: 0.3947
 135/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 751us/step - accuracy: 0.8616 - loss: 0.4133
 205/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 741us/step - accuracy: 0.8573 - loss: 0.4214
 276/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 733us/step - accuracy: 0.8555 - loss: 0.4239
 346/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 730us/step - accuracy: 0.8543 - loss: 0.4253
 414/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 731us/step - accuracy: 0.8535 - loss: 0.4263
 482/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 732us/step - accuracy: 0.8531 - loss: 0.4267
 550/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 734us/step - accuracy: 0.8528 - loss: 0.4270
 616/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8527 - loss: 0.4269
 684/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8528 - loss: 0.4267
 752/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 739us/step - accuracy: 0.8528 - loss: 0.4266
 821/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8528 - loss: 0.4265
 890/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8529 - loss: 0.4264
 957/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8530 - loss: 0.4261
1025/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8531 - loss: 0.4257
1092/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 739us/step - accuracy: 0.8533 - loss: 0.4253
1159/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 740us/step - accuracy: 0.8534 - loss: 0.4249
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1225/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 741us/step - accuracy: 0.8535 - loss: 0.4245
1291/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 743us/step - accuracy: 0.8536 - loss: 0.4242
1356/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 744us/step - accuracy: 0.8537 - loss: 0.4239
1420/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 746us/step - accuracy: 0.8538 - loss: 0.4235
1485/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 747us/step - accuracy: 0.8539 - loss: 0.4232
1549/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 749us/step - accuracy: 0.8540 - loss: 0.4228
1614/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 750us/step - accuracy: 0.8541 - loss: 0.4225
1679/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 751us/step - accuracy: 0.8542 - loss: 0.4222
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 810us/step - accuracy: 0.8543 - loss: 0.4220 - val_accuracy: 0.8488 - val_loss: 0.4176
Epoch 5/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.8438 - loss: 0.4341
  65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 784us/step - accuracy: 0.8733 - loss: 0.3710
 131/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 774us/step - accuracy: 0.8668 - loss: 0.3883
 197/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 770us/step - accuracy: 0.8629 - loss: 0.3969
 264/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 767us/step - accuracy: 0.8615 - loss: 0.3996
 330/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 767us/step - accuracy: 0.8606 - loss: 0.4012
 397/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 765us/step - accuracy: 0.8600 - loss: 0.4024
 463/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8597 - loss: 0.4030
 529/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8596 - loss: 0.4034
 595/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8595 - loss: 0.4036
 662/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8596 - loss: 0.4035
 727/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8598 - loss: 0.4035
 793/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8599 - loss: 0.4035
 859/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8600 - loss: 0.4034
 926/1719 ━━━━
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━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8601 - loss: 0.4033
991/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8602 - loss:
0.4031
1056/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy:
0.8603 - loss: 0.4028
1122/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/ste
p - accuracy: 0.8605 - loss: 0.4025
1189/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 764us/step - accuracy: 0.8606 - loss: 0.4021
1255/1719 ━━━━
━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8607 - loss: 0.4019
1
321/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8608 - loss:
0.4016
1388/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy:
0.8609 - loss: 0.4013
1456/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 762us/ste
p - accuracy: 0.8611 - loss: 0.4010
1524/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 761us/step - accuracy: 0.8612 - loss: 0.4007
1592/1719 ━━━━
━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8613 - loss: 0.4004
1
659/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8614 - loss:
0.4001
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 816us/step - accuracy:
0.8615 - loss: 0.3999 - val_accuracy: 0.8532 - val_loss: 0.4043
Epoch 6/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.8438 - loss:
0.4187
  66/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 774us/step - accuracy:
0.8770 - loss: 0.3533
 132/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 767us/ste
p - accuracy: 0.8708 - loss: 0.3701
 199/1719 ━━━━━━━━━━━━━━━━━━━
━ 1s 763us/step - accuracy: 0.8675 - loss: 0.3785
 264/1719 ━━━━
━━━━━━━━━━━━━━━ 1s 765us/step - accuracy: 0.8664 - loss: 0.3811

331/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 763us/step - accuracy: 0.8655 - loss:
0.3828
 397/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 764us/step - accuracy:
0.8651 - loss: 0.3840
 462/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/ste
p - accuracy: 0.8649 - loss: 0.3848
 527/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 766us/step - accuracy: 0.8648 - loss: 0.3852
 591/1719 ━━━━
━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.8648 - loss: 0.3854

657/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.8649 - loss:
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0.3854□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8650 - loss: 0.3854□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8651 - loss: 0.3854□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.8653 - loss: 0.3855□□□□□□□□
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981/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.8654 - loss:
0.3853□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8655 - loss: 0.3851□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8657 - loss: 0.3848□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 775us/step - accuracy: 0.8658 - loss: 0.3845□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.8658 - loss: 0.3843□□□□□□□□
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300/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.8659 - loss:
0.3841□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8659 - loss: 0.3839□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8660 - loss: 0.3836□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 773us/step - accuracy: 0.8661 - loss: 0.3833□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.8662 - loss: 0.3831□□□□□□□□
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636/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.8663 - loss:
0.3829□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□1703/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy:
0.8664 - loss: 0.3827□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 825us/ste
p - accuracy: 0.8664 - loss: 0.3826 - val_accuracy: 0.8572 - val_loss:
0.3937
Epoch 7/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.8438 - loss:
0.4098□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□  68/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 756us/step - accuracy:
0.8832 - loss: 0.3389□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8771 - loss: 0.3551□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 754us/step - accuracy: 0.8737 - loss: 0.3632□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 269/1719 ━━━━━
━━━━━━━━━━━━━━━ 1s 751us/step - accuracy: 0.8724 - loss: 0.3660□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
336/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 752us/step - accuracy: 0.8714 - loss:
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0.3677□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 402/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 754us/step - accuracy:
0.8709 - loss: 0.3690□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 470/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 752us/ste
p - accuracy: 0.8706 - loss: 0.3697□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 753us/step - accuracy: 0.8704 - loss: 0.3702□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 750us/step - accuracy: 0.8704 - loss: 0.3704□□□□□□□□
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675/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 748us/step - accuracy: 0.8704 - loss:
0.3704□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 743/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 747us/step - accuracy:
0.8705 - loss: 0.3705□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 812/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 746us/ste
p - accuracy: 0.8706 - loss: 0.3705□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 746us/step - accuracy: 0.8706 - loss: 0.3706□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.8707 - loss: 0.3706□□□□□□□□
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015/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 745us/step - accuracy: 0.8708 - loss:
0.3704□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8709 - loss: 0.3702□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1152/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 744us/ste
p - accuracy: 0.8710 - loss: 0.3700□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 744us/step - accuracy: 0.8710 - loss: 0.3697□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 743us/step - accuracy: 0.8711 - loss: 0.3696□□□□□□□□
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355/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 744us/step - accuracy: 0.8711 - loss:
0.3694□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□1423/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 743us/step - accuracy:
0.8712 - loss: 0.3691□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1489/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 744us/ste
p - accuracy: 0.8712 - loss: 0.3689□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 744us/step - accuracy: 0.8713 - loss: 0.3687□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□1625/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 744us/step - accuracy: 0.8713 - loss: 0.3685□□□□□□□□
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693/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 743us/step - accuracy: 0.8714 - loss:
0.3683□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 799us/step - accuracy:
0.8714 - loss: 0.3682 - val_accuracy: 0.8584 - val_loss: 0.3851
Epoch 8/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.8438 - loss:
0.4052□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□  69/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 743us/step - accuracy:
0.8875 - loss: 0.3271□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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 136/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 748us/step - accuracy: 0.8820 - loss: 0.3428
 205/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 743us/step - accuracy: 0.8792 - loss: 0.3506
 273/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 742us/step - accuracy: 0.8779 - loss: 0.3533
 341/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 742us/step - accuracy: 0.8769 - loss: 0.3550
 409/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 741us/step - accuracy: 0.8763 - loss: 0.3564
 478/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 739us/step - accuracy: 0.8760 - loss: 0.3572
 547/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8757 - loss: 0.3577
 616/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8756 - loss: 0.3578
 685/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8756 - loss: 0.3578
 752/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8756 - loss: 0.3579
 821/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8756 - loss: 0.3580
 890/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8755 - loss: 0.3581
 957/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8755 - loss: 0.3581
1026/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8755 - loss: 0.3580
1095/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8756 - loss: 0.3578
1164/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8756 - loss: 0.3575
1232/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8757 - loss: 0.3574
1299/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8757 - loss: 0.3572
1367/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 738us/step - accuracy: 0.8757 - loss: 0.3570
1436/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8757 - loss: 0.3568
1505/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 737us/step - accuracy: 0.8758 - loss: 0.3566
1574/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 736us/step - accuracy: 0.8758 - loss: 0.3564
1643/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 736us/step - accuracy: 0.8758 - loss: 0.3562
1712/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 736us/step - accuracy: 0.8758 - loss:
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0.3560▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8758 - loss: 0.3560 - val_accuracy: 0.8604 - val_loss: 0.3788
Epoch 9/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.8750 - loss:
0.3841▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8905 - loss: 0.3144▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8845 - loss: 0.3299▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 1s 751us/step - accuracy: 0.8817 - loss: 0.3386▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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337/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 749us/step - accuracy: 0.8796 - loss:
0.3433▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8792 - loss: 0.3448▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8789 - loss: 0.3457▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 748us/step - accuracy: 0.8787 - loss: 0.3462▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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671/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 751us/step - accuracy: 0.8786 - loss:
0.3465▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8786 - loss: 0.3466▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8786 - loss: 0.3467▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 753us/step - accuracy: 0.8786 - loss: 0.3469▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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002/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 755us/step - accuracy: 0.8786 - loss:
0.3469▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8786 - loss: 0.3467▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8787 - loss: 0.3466▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 756us/step - accuracy: 0.8787 - loss: 0.3464▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 756us/step - accuracy: 0.8787 - loss: 0.3463▯▯▯▯▯▯▯▯
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334/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 756us/step - accuracy: 0.8788 - loss:
0.3461▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8788 - loss: 0.3459▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8789 - loss: 0.3457□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 756us/step - accuracy: 0.8789 - loss: 0.3455□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8789 - loss: 0.3454□□□□□□□□
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665/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 756us/step - accuracy: 0.8790 - loss:
0.3452□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8790 - loss: 0.3451 - val_accuracy: 0.8620 - val_loss: 0.3739
Epoch 10/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.8750 - loss:
0.3685□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8917 - loss: 0.3041□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8868 - loss: 0.3192□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 765us/step - accuracy: 0.8839 - loss: 0.3277□□□□□□□□□□□□□□□□□□□□□□
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330/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 766us/step - accuracy: 0.8820 - loss:
0.3326□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8815 - loss: 0.3342□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8813 - loss: 0.3352□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 763us/step - accuracy: 0.8811 - loss: 0.3358□□□□□□□□□□□□□□□□□□□□□□
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661/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8810 - loss:
0.3363□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8811 - loss: 0.3364□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8811 - loss: 0.3365□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 762us/step - accuracy: 0.8810 - loss: 0.3367□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.8810 - loss: 0.3368□□□□□□□□
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995/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8810 - loss:
0.3368□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8811 - loss: 0.3367□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1129/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/ste
p - accuracy: 0.8812 - loss: 0.3365□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 758us/step - accuracy: 0.8812 - loss: 0.3363
1261/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.8812 - loss: 0.3362
1328/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8813 - loss: 0.3361
1396/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8813 - loss: 0.3359
1462/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8814 - loss: 0.3357
1529/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8814 - loss: 0.3356
1597/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.8814 - loss: 0.3354
1661/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 758us/step - accuracy: 0.8815 - loss: 0.3353
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 819us/step - accuracy: 0.8815 - loss: 0.3352 - val_accuracy: 0.8640 - val_loss: 0.3690
Epoch 11/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9062 - loss: 0.3526
  65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 791us/step - accuracy: 0.8956 - loss: 0.2945
 130/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 781us/step - accuracy: 0.8895 - loss: 0.3093
 194/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 782us/step - accuracy: 0.8864 - loss: 0.3179
 262/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 772us/step - accuracy: 0.8854 - loss: 0.3211
 330/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 765us/step - accuracy: 0.8846 - loss: 0.3232
 396/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 764us/step - accuracy: 0.8842 - loss: 0.3248
 462/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8839 - loss: 0.3258
 527/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8838 - loss: 0.3265
 593/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8837 - loss: 0.3269
 658/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8838 - loss: 0.3270
 724/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8838 - loss: 0.3271
 789/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8838 - loss: 0.3273
 855/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8838 - loss: 0.3274
 923/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8838 - loss: 0.3276
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992/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8838 - loss:
0.3276□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8839 - loss: 0.3275□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8840 - loss: 0.3273□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 761us/step - accuracy: 0.8840 - loss: 0.3272□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8840 - loss: 0.3271□□□□□□□
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325/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.8841 - loss:
0.3270□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8841 - loss: 0.3268□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8842 - loss: 0.3266□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 759us/step - accuracy: 0.8842 - loss: 0.3265□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.8842 - loss: 0.3263□□□□□□□
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661/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.8843 - loss:
0.3262□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 814us/step - accuracy:
0.8843 - loss: 0.3261 - val_accuracy: 0.8662 - val_loss: 0.3648
Epoch 12/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9062 - loss:
0.3407□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9027 - loss: 0.2855□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8965 - loss: 0.3000□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 775us/step - accuracy: 0.8930 - loss: 0.3085□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 1s 767us/step - accuracy: 0.8914 - loss: 0.3118□□□□□□□
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331/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 765us/step - accuracy: 0.8902 - loss:
0.3139□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 398/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 763us/step - accuracy:
0.8894 - loss: 0.3156□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 463/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/ste
p - accuracy: 0.8889 - loss: 0.3167□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 761us/step - accuracy: 0.8884 - loss: 0.3174□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.8882 - loss: 0.3179□□□□□□□
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659/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8881 - loss:
0.3180□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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 721/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.8880 - loss: 0.3181
 786/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.8879 - loss: 0.3183
 851/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.8878 - loss: 0.3185
 916/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.8877 - loss: 0.3187
 983/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.8877 - loss: 0.3187
1049/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.8876 - loss: 0.3186
1116/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.8877 - loss: 0.3185
1184/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.8877 - loss: 0.3184
1251/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.8876 - loss: 0.3183
1315/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.8876 - loss: 0.3182
1383/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8876 - loss: 0.3181
1451/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8877 - loss: 0.3179
1517/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.8877 - loss: 0.3178
1585/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8877 - loss: 0.3177
1652/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8877 - loss: 0.3176
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 818us/step - accuracy: 0.8877 - loss: 0.3175 - val_accuracy: 0.8668 - val_loss: 0.3611
Epoch 13/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9062 - loss: 0.3295
  66/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 773us/step - accuracy: 0.9041 - loss: 0.2776
 133/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 765us/step - accuracy: 0.8974 - loss: 0.2922
 199/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 763us/step - accuracy: 0.8940 - loss: 0.3004
 263/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 768us/step - accuracy: 0.8926 - loss: 0.3034
 327/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 771us/step - accuracy: 0.8915 - loss: 0.3055
 394/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 767us/step - accuracy: 0.8908 - loss: 0.3072
 461/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/ste
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p - accuracy: 0.8903 - loss: 0.3084□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 763us/step - accuracy: 0.8900 - loss: 0.3092□□□□□□□□□□□□□□□□□□□□□□
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660/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8897 - loss:
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0.8897 - loss: 0.3100□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8896 - loss: 0.3102□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 764us/step - accuracy: 0.8895 - loss: 0.3104□□□□□□□□□□□□□□□□□□□□□□
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987/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.8894 - loss:
0.3106□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8895 - loss: 0.3106□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8895 - loss: 0.3105□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 768us/step - accuracy: 0.8895 - loss: 0.3104□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.8895 - loss: 0.3103□□□□□□□□
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307/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.8896 - loss:
0.3102□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8896 - loss: 0.3102□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8896 - loss: 0.3100□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 785us/step - accuracy: 0.8897 - loss: 0.3099□□□□□□□□□□□□□□□□□□□□□□
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604/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.8897 - loss:
0.3097□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8897 - loss: 0.3096□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8897 - loss: 0.3096 - val_accuracy: 0.8678 - val_loss:
0.3591
Epoch 14/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 12ms/step - accuracy: 0.9375 - loss:
0.3176□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9079 - loss: 0.2706□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9004 - loss: 0.2845▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 1s 777us/step - accuracy: 0.8970 - loss: 0.2928▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 1s 771us/step - accuracy: 0.8956 - loss: 0.2960▯▯▯▯▯▯▯
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327/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 773us/step - accuracy: 0.8945 - loss:
0.2981▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8939 - loss: 0.2998▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8935 - loss: 0.3010▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 775us/step - accuracy: 0.8931 - loss: 0.3018▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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656/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.8928 - loss:
0.3024▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8927 - loss: 0.3026▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8925 - loss: 0.3028▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 768us/step - accuracy: 0.8924 - loss: 0.3030▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8923 - loss: 0.3033▯▯▯▯▯▯▯
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987/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.8923 - loss:
0.3033▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8922 - loss: 0.3032▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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315/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.8922 - loss:
0.3030▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8922 - loss: 0.3029▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.8923 - loss: 0.3028▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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645/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8923 - loss:
0.3025▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.8923 - loss: 0.3024□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8923 - loss: 0.3024 - val_accuracy: 0.8686 - val_loss:
0.3569
Epoch 15/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9375 - loss:
0.3072□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9087 - loss: 0.2641□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9020 - loss: 0.2780□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 759us/step - accuracy: 0.8986 - loss: 0.2860□□□□□□□□□□□□□□□□□□□□□□
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335/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 754us/step - accuracy: 0.8961 - loss:
0.2913□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8955 - loss: 0.2930□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8951 - loss: 0.2941□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 774us/step - accuracy: 0.8947 - loss: 0.2948□□□□□□□□□□□□□□□□□□□□□□
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642/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.8944 - loss:
0.2955□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8943 - loss: 0.2957□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8942 - loss: 0.2959□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 786us/step - accuracy: 0.8941 - loss: 0.2961□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 787us/step - accuracy: 0.8940 - loss: 0.2963□□□□□□□□
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961/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 788us/step - accuracy: 0.8940 - loss:
0.2964□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8940 - loss: 0.2965□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8939 - loss: 0.2964□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 787us/step - accuracy: 0.8940 - loss: 0.2963□□□□□□□□□□□□□□□□□□□□□□
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281/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 788us/step - accuracy: 0.8940 - loss:
0.2963□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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1346/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 787us/step - accuracy: 0.8940 - loss: 0.2962
1412/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.8940 - loss: 0.2961
1479/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 785us/step - accuracy: 0.8941 - loss: 0.2960
1545/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 784us/step - accuracy: 0.8941 - loss: 0.2959
1612/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.8941 - loss: 0.2958
1679/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 781us/step - accuracy: 0.8941 - loss: 0.2957
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 838us/step - accuracy: 0.8941 - loss: 0.2957 - val_accuracy: 0.8684 - val_loss: 0.3557
Epoch 16/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9375 - loss: 0.3022
  65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 788us/step - accuracy: 0.9128 - loss: 0.2575
 131/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 773us/step - accuracy: 0.9059 - loss: 0.2711
 198/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 766us/step - accuracy: 0.9019 - loss: 0.2794
 265/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 764us/step - accuracy: 0.9003 - loss: 0.2826
 333/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 760us/step - accuracy: 0.8990 - loss: 0.2847
 399/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 761us/step - accuracy: 0.8982 - loss: 0.2865
 464/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.8977 - loss: 0.2876
 529/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.8974 - loss: 0.2884
 594/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.8971 - loss: 0.2888
 659/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.8970 - loss: 0.2890
 721/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.8969 - loss: 0.2892
 782/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.8968 - loss: 0.2894
 843/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.8967 - loss: 0.2896
 905/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 781us/step - accuracy: 0.8966 - loss: 0.2899
 969/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 782us/step - accuracy: 0.8965 - loss: 0.2900
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0.8965 - loss: 0.2900□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8964 - loss: 0.2900□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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285/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 785us/step - accuracy: 0.8964 - loss:
0.2898□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8964 - loss: 0.2898□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8965 - loss: 0.2897□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 789us/step - accuracy: 0.8965 - loss: 0.2896□□□□□□□□□□□□□□□□□□□□□□
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600/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 788us/step - accuracy: 0.8966 - loss:
0.2894□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8966 - loss: 0.2894□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.8966 - loss: 0.2893 - val_accuracy: 0.8708 - val_loss:
0.3539
Epoch 17/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 20s 12ms/step - accuracy: 0.9375 - loss:
0.2907□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9134 - loss: 0.2506□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9081 - loss: 0.2631□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 800us/step - accuracy: 0.9043 - loss: 0.2721□□□□□□□□□□□□□□□□□□□□□□
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318/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 798us/step - accuracy: 0.9014 - loss:
0.2777□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9006 - loss: 0.2795□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9000 - loss: 0.2809□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 795us/step - accuracy: 0.8997 - loss: 0.2818□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 795us/step - accuracy: 0.8994 - loss: 0.2823□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 
639/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 791us/step - accuracy: 0.8993 - loss:
0.2826□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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 705/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 788us/step - accuracy: 0.8992 - loss: 0.2828
 771/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.8991 - loss: 0.2830
 838/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.8990 - loss: 0.2833
 905/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 781us/step - accuracy: 0.8989 - loss: 0.2836
 973/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.8988 - loss: 0.2837
1041/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.8988 - loss: 0.2837
1109/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 774us/step - accuracy: 0.8988 - loss: 0.2837
1176/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.8988 - loss: 0.2837
1242/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.8988 - loss: 0.2836
1306/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.8988 - loss: 0.2836
1370/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 773us/step - accuracy: 0.8988 - loss: 0.2835
1425/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.8988 - loss: 0.2835
1486/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 780us/step - accuracy: 0.8989 - loss: 0.2834
1553/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.8989 - loss: 0.2833
1619/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.8989 - loss: 0.2832
1686/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.8989 - loss: 0.2832
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 832us/step - accuracy: 0.8989 - loss: 0.2832 - val_accuracy: 0.8704 - val_loss: 0.3535
Epoch 18/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 12ms/step - accuracy: 0.9375 - loss: 0.2860
  65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 790us/step - accuracy: 0.9151 - loss: 0.2462
 132/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 769us/step - accuracy: 0.9093 - loss: 0.2593
 193/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 788us/step - accuracy: 0.9063 - loss: 0.2669
 242/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 844us/step - accuracy: 0.9052 - loss: 0.2696
 290/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 880us/step - accuracy: 0.9042 - loss: 0.2714
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0.9033 - loss: 0.2731□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9026 - loss: 0.2746□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 862us/step - accuracy: 0.9021 - loss: 0.2757□□□□□□□□□□□□□□□□□□□□□□
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593/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 855us/step - accuracy: 0.9016 - loss:
0.2768□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9015 - loss: 0.2770□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 714/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 851us/ste
p - accuracy: 0.9013 - loss: 0.2772□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 843us/step - accuracy: 0.9012 - loss: 0.2774□□□□□□□□□□□□□□□□□□□□□□
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908/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.9009 - loss:
0.2779□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9008 - loss: 0.2780□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1029/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/ste
p - accuracy: 0.9008 - loss: 0.2780□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 836us/step - accuracy: 0.9007 - loss: 0.2780□□□□□□□□□□□□□□□□□□□□□□
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210/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.9007 - loss:
0.2780□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9007 - loss: 0.2780□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9007 - loss: 0.2779□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 835us/step - accuracy: 0.9007 - loss: 0.2778□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 835us/step - accuracy: 0.9007 - loss: 0.2778□□□□□□□□
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515/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 834us/step - accuracy: 0.9007 - loss:
0.2777□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9007 - loss: 0.2776□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9007 - loss: 0.2776□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 831us/step - accuracy: 0.9007 - loss: 0.2775□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□1719/1719 ━━━━━
━━━━━━━━━━━━━━━ 2s 894us/step - accuracy: 0.9007 - loss: 0.2775 - val_a
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ccuracy: 0.8722 - val_loss: 0.3518
Epoch 19/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 21s 12ms/step - accuracy: 0.9375 - loss:
0.2799□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9180 - loss: 0.2392□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 118/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 861us/ste
p - accuracy: 0.9129 - loss: 0.2508□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 179/1719 ━━━━━━━━━━━━━━━━━━━
━ 1s 848us/step - accuracy: 0.9090 - loss: 0.2601□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 240/1719 ━━━━━
━━━━━━━━━━━━━━━ 1s 841us/step - accuracy: 0.9074 - loss: 0.2637□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
302/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 836us/step - accuracy: 0.9062 - loss:
0.2661□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 361/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 838us/step - accuracy:
0.9054 - loss: 0.2677□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 421/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 839us/ste
p - accuracy: 0.9048 - loss: 0.2692□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 835us/step - accuracy: 0.9043 - loss: 0.2702□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 830us/step - accuracy: 0.9040 - loss: 0.2709□□□□□□□□
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611/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 825us/step - accuracy: 0.9038 - loss:
0.2712□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 678/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 819us/step - accuracy:
0.9036 - loss: 0.2714□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 741/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 817us/ste
p - accuracy: 0.9035 - loss: 0.2716□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 847us/step - accuracy: 0.9034 - loss: 0.2718□□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 845us/step - accuracy: 0.9033 - loss: 0.2720□□□□□□□□
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898/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 843us/step - accuracy: 0.9031 - loss:
0.2723□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 962/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 839us/step - accuracy:
0.9030 - loss: 0.2724□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1023/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 838us/ste
p - accuracy: 0.9030 - loss: 0.2725□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 839us/step - accuracy: 0.9029 - loss: 0.2725□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□1142/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 839us/step - accuracy: 0.9029 - loss: 0.2724□□□□□□□□
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203/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 838us/step - accuracy: 0.9029 - loss:
0.2724□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□1268/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 835us/step - accuracy:
0.9028 - loss: 0.2724□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1329/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 834us/ste
p - accuracy: 0.9028 - loss: 0.2724□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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1389/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 834us/step - accuracy: 0.9029 - loss: 0.2723
1448/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 835us/step - accuracy: 0.9029 - loss: 0.2722
1506/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.9029 - loss: 0.2722
1566/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.9029 - loss: 0.2721
1626/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.9029 - loss: 0.2721
1687/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 836us/step - accuracy: 0.9029 - loss: 0.2721
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 2s 898us/step - accuracy: 0.9029 - loss: 0.2720 - val_accuracy: 0.8730 - val_loss: 0.3520
Epoch 20/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 20s 12ms/step - accuracy: 0.9375 - loss: 0.2773
  62/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 822us/step - accuracy: 0.9210 - loss: 0.2348
 125/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 812us/step - accuracy: 0.9148 - loss: 0.2467
 190/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 802us/step - accuracy: 0.9110 - loss: 0.2554
 251/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 807us/step - accuracy: 0.9092 - loss: 0.2587
 312/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 811us/step - accuracy: 0.9079 - loss: 0.2608
 374/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 810us/step - accuracy: 0.9070 - loss: 0.2625
 436/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 810us/step - accuracy: 0.9064 - loss: 0.2640
 498/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 811us/step - accuracy: 0.9060 - loss: 0.2649
 559/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 813us/step - accuracy: 0.9057 - loss: 0.2656
 621/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 812us/step - accuracy: 0.9055 - loss: 0.2659
 682/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 814us/step - accuracy: 0.9054 - loss: 0.2661
 742/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 815us/step - accuracy: 0.9053 - loss: 0.2663
 803/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 816us/step - accuracy: 0.9051 - loss: 0.2665
 864/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 817us/step - accuracy: 0.9050 - loss: 0.2668
 925/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 818us/step - accuracy: 0.9049 - loss: 0.2670
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 988/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 817us/step - accuracy: 0.9048 - loss: 0.2671
1049/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 817us/step - accuracy: 0.9048 - loss: 0.2671
1113/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 816us/step - accuracy: 0.9047 - loss: 0.2671
1179/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 813us/step - accuracy: 0.9047 - loss: 0.2671
1244/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 811us/step - accuracy: 0.9047 - loss: 0.2671
1308/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 809us/step - accuracy: 0.9046 - loss: 0.2670
1370/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 810us/step - accuracy: 0.9046 - loss: 0.2670
1432/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 810us/step - accuracy: 0.9047 - loss: 0.2669
1497/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 808us/step - accuracy: 0.9047 - loss: 0.2668
1563/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 806us/step - accuracy: 0.9047 - loss: 0.2668
1628/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 805us/step - accuracy: 0.9047 - loss: 0.2667
1694/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 804us/step - accuracy: 0.9047 - loss: 0.2667
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 861us/step - accuracy: 0.9047 - loss: 0.2667 - val_accuracy: 0.8720 - val_loss: 0.3499
Epoch 21/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9688 - loss: 0.2660
  65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 792us/step - accuracy: 0.9242 - loss: 0.2300
 130/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 783us/step - accuracy: 0.9174 - loss: 0.2422
 195/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 780us/step - accuracy: 0.9135 - loss: 0.2502
 260/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 778us/step - accuracy: 0.9118 - loss: 0.2536
 323/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 781us/step - accuracy: 0.9105 - loss: 0.2557
 389/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 779us/step - accuracy: 0.9097 - loss: 0.2576
 450/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 784us/step - accuracy: 0.9091 - loss: 0.2589
 514/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 784us/step - accuracy: 0.9087 - loss: 0.2598
 579/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.9084 - loss: 0.2604
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 644/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 782us/step - accuracy: 0.9082 - loss: 0.2607
 710/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 780us/step - accuracy: 0.9081 - loss: 0.2609
 776/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.9080 - loss: 0.2612
 843/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.9078 - loss: 0.2615
 908/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.9077 - loss: 0.2618
 974/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.9076 - loss: 0.2619
1040/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.9075 - loss: 0.2620
1106/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 774us/step - accuracy: 0.9074 - loss: 0.2620
1172/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 774us/step - accuracy: 0.9074 - loss: 0.2620
1239/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.9073 - loss: 0.2620
1306/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.9073 - loss: 0.2620
1373/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.9073 - loss: 0.2619
1442/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.9073 - loss: 0.2618
1510/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.9073 - loss: 0.2618
1579/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9073 - loss: 0.2617
1645/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.9073 - loss: 0.2617
1713/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.9072 - loss: 0.2617
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 821us/step - accuracy: 0.9072 - loss: 0.2616 - val_accuracy: 0.8732 - val_loss: 0.3489
Epoch 22/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9688 - loss: 0.2588
  64/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 801us/step - accuracy: 0.9291 - loss: 0.2246
 130/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 779us/step - accuracy: 0.9204 - loss: 0.2369
 196/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 774us/step - accuracy: 0.9161 - loss: 0.2451
 263/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 770us/step - accuracy: 0.9140 - loss: 0.2487
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330/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 766us/step - accuracy: 0.9125 - loss: 0.2509
397/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 763us/step - accuracy: 0.9115 - loss: 0.2529
464/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 762us/step - accuracy: 0.9108 - loss: 0.2542
531/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.9104 - loss: 0.2551
598/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9101 - loss: 0.2556
665/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9099 - loss: 0.2559
730/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.9098 - loss: 0.2561
797/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9096 - loss: 0.2564
864/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9094 - loss: 0.2567
930/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9093 - loss: 0.2570
996/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9092 - loss: 0.2571
1059/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 762us/step - accuracy: 0.9091 - loss: 0.2571
1123/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 764us/step - accuracy: 0.9091 - loss: 0.2571
1187/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.9090 - loss: 0.2571
1253/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.9090 - loss: 0.2571
1318/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9089 - loss: 0.2571
1385/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.9089 - loss: 0.2570
1450/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9089 - loss: 0.2569
1516/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9089 - loss: 0.2569
1582/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9089 - loss: 0.2569
1647/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9089 - loss: 0.2568
1714/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 765us/step - accuracy: 0.9089 - loss: 0.2568
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 824us/step - accuracy: 0.9089 - loss: 0.2568 - val_accuracy: 0.8746 - val_loss: 0.3494
Epoch 23/30
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   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9688 - loss:
0.2519□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□  68/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 756us/step - accuracy:
0.9276 - loss: 0.2201□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 136/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 750us/ste
p - accuracy: 0.9202 - loss: 0.2327□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 752us/step - accuracy: 0.9163 - loss: 0.2403□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 1s 752us/step - accuracy: 0.9145 - loss: 0.2437□□□□□□□□
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335/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 758us/step - accuracy: 0.9132 - loss:
0.2458□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9124 - loss: 0.2477□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9118 - loss: 0.2491□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 761us/step - accuracy: 0.9115 - loss: 0.2500□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.9113 - loss: 0.2505□□□□□□□□
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662/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.9112 - loss:
0.2508□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9111 - loss: 0.2511□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9110 - loss: 0.2514□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 762us/step - accuracy: 0.9109 - loss: 0.2517□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 762us/step - accuracy: 0.9107 - loss: 0.2519□□□□□□□□
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994/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.9107 - loss:
0.2521□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9106 - loss: 0.2521□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9106 - loss: 0.2521□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 759us/step - accuracy: 0.9106 - loss: 0.2521□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9105 - loss: 0.2521□□□□□□□□
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327/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9105 - loss:
0.2521□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9105 - loss: 0.2520□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□1462/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/ste
p - accuracy: 0.9105 - loss: 0.2519□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 759us/step - accuracy: 0.9105 - loss: 0.2519□□□□□□□□□□□□□□□□□□□□□
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1595/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/step - accuracy: 0.9105 - loss: 0.2519
1664/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy: 0.9105 - loss: 0.2518
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 813us/step - accuracy: 0.9105 - loss: 0.2518 - val_accuracy: 0.8750 - val_loss: 0.3488
Epoch 24/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 18s 11ms/step - accuracy: 0.9688 - loss: 0.2443
  66/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 777us/step - accuracy: 0.9280 - loss: 0.2153
 131/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 777us/step - accuracy: 0.9208 - loss: 0.2273
 195/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 779us/step - accuracy: 0.9174 - loss: 0.2351
 260/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 777us/step - accuracy: 0.9156 - loss: 0.2386
 326/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 774us/step - accuracy: 0.9143 - loss: 0.2408
 392/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 773us/step - accuracy: 0.9135 - loss: 0.2428
 457/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 774us/step - accuracy: 0.9129 - loss: 0.2443
 523/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy: 0.9126 - loss: 0.2452
 588/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 773us/step - accuracy: 0.9124 - loss: 0.2458
 653/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 773us/step - accuracy: 0.9123 - loss: 0.2461
 720/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.9122 - loss: 0.2463
 786/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.9121 - loss: 0.2466
 852/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.9120 - loss: 0.2469
 919/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.9119 - loss: 0.2472
 985/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.9118 - loss: 0.2474
1050/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/step - accuracy: 0.9118 - loss: 0.2474
1116/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.9118 - loss: 0.2474
1182/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.9118 - loss: 0.2474
1249/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.9117 - loss: 0.2474
1
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313/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 768us/step - accuracy: 0.9117 - loss:
0.2474
1380/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy:
0.9118 - loss: 0.2474
1447/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/ste
p - accuracy: 0.9118 - loss: 0.2473
1513/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 766us/step - accuracy: 0.9118 - loss: 0.2473
1578/1719 ━━━━
━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9118 - loss: 0.2472
1
643/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.9118 - loss:
0.2472
1709/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy:
0.9118 - loss: 0.2472
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 823us/ste
p - accuracy: 0.9118 - loss: 0.2472 - val_accuracy: 0.8760 - val_loss:
0.3457
Epoch 25/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9688 - loss:
0.2290
  70/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 733us/step - accuracy:
0.9309 - loss: 0.2111
 138/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 739us/ste
p - accuracy: 0.9237 - loss: 0.2237
 205/1719 ━━━━━━━━━━━━━━━━━━━
━ 1s 744us/step - accuracy: 0.9201 - loss: 0.2310
 271/1719 ━━━━
━━━━━━━━━━━━━━━━ 1s 747us/step - accuracy: 0.9183 - loss: 0.2343

336/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 752us/step - accuracy: 0.9171 - loss:
0.2363
 402/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 754us/step - accuracy:
0.9161 - loss: 0.2382
 469/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 753us/ste
p - accuracy: 0.9156 - loss: 0.2396
 535/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 754us/step - accuracy: 0.9152 - loss: 0.2405
 601/1719 ━━━━
━━━━━━━━━━━━━━━━ 0s 755us/step - accuracy: 0.9149 - loss: 0.2410

668/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 755us/step - accuracy: 0.9147 - loss:
0.2413
 733/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 757us/step - accuracy:
0.9146 - loss: 0.2416
 798/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 759us/ste
p - accuracy: 0.9144 - loss: 0.2419
 864/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 759us/step - accuracy: 0.9143 - loss: 0.2422
 930/1719 ━━━━
━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9141 - loss: 0.2425

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996/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 760us/step - accuracy: 0.9140 - loss:
0.2426▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.9139 - loss: 0.2426▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1128/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/ste
p - accuracy: 0.9139 - loss: 0.2426▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 762us/step - accuracy: 0.9138 - loss: 0.2427▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.9138 - loss: 0.2427▯▯▯▯▯▯▯▯
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324/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy: 0.9138 - loss:
0.2427▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1390/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 763us/step - accuracy:
0.9138 - loss: 0.2426▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1458/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 762us/ste
p - accuracy: 0.9138 - loss: 0.2426▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 762us/step - accuracy: 0.9138 - loss: 0.2426▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.9137 - loss: 0.2425▯▯▯▯▯▯▯▯
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659/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 761us/step - accuracy: 0.9137 - loss:
0.2425▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 817us/step - accuracy:
0.9137 - loss: 0.2425 - val_accuracy: 0.8754 - val_loss: 0.3472
Epoch 26/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9688 - loss:
0.2239▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯  67/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 767us/step - accuracy:
0.9338 - loss: 0.2065▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 132/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 772us/ste
p - accuracy: 0.9261 - loss: 0.2184▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 194/1719 ━━━━━━━━━━━━━━━━━━━
━ 1s 784us/step - accuracy: 0.9225 - loss: 0.2259▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 260/1719 ━━━━━
━━━━━━━━━━━━━━━ 1s 777us/step - accuracy: 0.9206 - loss: 0.2294▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
325/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 776us/step - accuracy: 0.9193 - loss:
0.2316▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯ 391/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 773us/step - accuracy:
0.9184 - loss: 0.2336▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 455/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/ste
p - accuracy: 0.9179 - loss: 0.2350▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 517/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 780us/step - accuracy: 0.9175 - loss: 0.2359▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 582/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.9173 - loss: 0.2365▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
647/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9171 - loss:
0.2369▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯ 714/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy:
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0.9169 - loss: 0.2371▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 780/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/ste
p - accuracy: 0.9168 - loss: 0.2374▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 846/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 774us/step - accuracy: 0.9166 - loss: 0.2377▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 911/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.9164 - loss: 0.2380▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
978/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 773us/step - accuracy: 0.9163 - loss:
0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1044/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 773us/step - accuracy:
0.9162 - loss: 0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1110/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/ste
p - accuracy: 0.9162 - loss: 0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 771us/step - accuracy: 0.9161 - loss: 0.2383▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.9160 - loss: 0.2383▯▯▯▯▯▯▯▯
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307/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.9160 - loss:
0.2383▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1373/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy:
0.9160 - loss: 0.2383▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1439/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/ste
p - accuracy: 0.9160 - loss: 0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 770us/step - accuracy: 0.9159 - loss: 0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1569/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.9159 - loss: 0.2382▯▯▯▯▯▯▯▯
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633/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 771us/step - accuracy: 0.9159 - loss:
0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯1697/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 772us/step - accuracy:
0.9158 - loss: 0.2382▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 830us/ste
p - accuracy: 0.9158 - loss: 0.2382 - val_accuracy: 0.8756 - val_loss:
0.3474
Epoch 27/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 20s 12ms/step - accuracy: 0.9688 - loss:
0.2126▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯  65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 783us/step - accuracy:
0.9353 - loss: 0.2013▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 128/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 790us/ste
p - accuracy: 0.9283 - loss: 0.2129▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 1s 783us/step - accuracy: 0.9244 - loss: 0.2212▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 259/1719 ━━━━━
━━━━━━━━━━━━━━━ 1s 781us/step - accuracy: 0.9226 - loss: 0.2247▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
325/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 778us/step - accuracy: 0.9213 - loss:
0.2269▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯ 391/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 776us/step - accuracy:
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0.9203 - loss: 0.2289
 456/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/ste
p - accuracy: 0.9196 - loss: 0.2304
 521/1719 ━━━━━━━━━━━━━━━━━━━━
━ 0s 776us/step - accuracy: 0.9192 - loss: 0.2314
 587/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.9188 - loss: 0.2320
651/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.9186 - loss:
0.2323
 715/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/step - accuracy:
0.9185 - loss: 0.2326
 778/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/ste
p - accuracy: 0.9183 - loss: 0.2329
 843/1719 ━━━━━━━━━━━━━━━━━━━━
━ 0s 779us/step - accuracy: 0.9181 - loss: 0.2332
 908/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9179 - loss: 0.2335
973/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9177 - loss:
0.2337
1037/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy:
0.9176 - loss: 0.2338
1102/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/ste
p - accuracy: 0.9175 - loss: 0.2338
1165/1719 ━━━━━━━━━━━━━━━━━━━━
━ 0s 779us/step - accuracy: 0.9175 - loss: 0.2338
1232/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9174 - loss: 0.2338
1
297/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9173 - loss:
0.2339
1362/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 778us/step - accuracy:
0.9173 - loss: 0.2338
1428/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/ste
p - accuracy: 0.9173 - loss: 0.2338
1494/1719 ━━━━━━━━━━━━━━━━━━━━
━ 0s 776us/step - accuracy: 0.9173 - loss: 0.2338
1558/1719 ━━━━━
━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.9172 - loss: 0.2338
1
623/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.9172 - loss:
0.2337
1687/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/step - accuracy:
0.9172 - loss: 0.2338
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 835us/ste
p - accuracy: 0.9172 - loss: 0.2338 - val_accuracy: 0.8772 - val_loss:
0.3464
Epoch 28/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9688 - loss:
0.2090
   65/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 788us/step - accuracy:
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0.9367 - loss: 0.1978□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 129/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 785us/ste
p - accuracy: 0.9296 - loss: 0.2093□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 784us/step - accuracy: 0.9258 - loss: 0.2173□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 1s 783us/step - accuracy: 0.9239 - loss: 0.2208□□□□□□□□
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324/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 782us/step - accuracy: 0.9226 - loss:
0.2229□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9218 - loss: 0.2248□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9211 - loss: 0.2263□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 786us/step - accuracy: 0.9207 - loss: 0.2273□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.9204 - loss: 0.2279□□□□□□□□
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643/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 785us/step - accuracy: 0.9202 - loss:
0.2282□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9201 - loss: 0.2285□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9199 - loss: 0.2287□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 785us/step - accuracy: 0.9197 - loss: 0.2290□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 785us/step - accuracy: 0.9196 - loss: 0.2294□□□□□□□□
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963/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 786us/step - accuracy: 0.9194 - loss:
0.2296□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9193 - loss: 0.2297□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9193 - loss: 0.2297□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 783us/step - accuracy: 0.9192 - loss: 0.2297□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.9191 - loss: 0.2297□□□□□□□□
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288/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.9191 - loss:
0.2298□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9191 - loss: 0.2298□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9191 - loss: 0.2297□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 784us/step - accuracy: 0.9190 - loss: 0.2297□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.9190 - loss: 0.2297□□□□□□□□
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609/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 783us/step - accuracy: 0.9190 - loss:
0.2296▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.9190 - loss: 0.2297▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.9190 - loss: 0.2297 - val_accuracy: 0.8774 - val_loss:
0.3459
Epoch 29/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 12ms/step - accuracy: 0.9688 - loss:
0.2021▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.9373 - loss: 0.1931▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯ 128/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 791us/ste
p - accuracy: 0.9306 - loss: 0.2048▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 1s 782us/step - accuracy: 0.9270 - loss: 0.2130▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 1s 780us/step - accuracy: 0.9252 - loss: 0.2165▯▯▯▯▯▯▯▯
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324/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 780us/step - accuracy: 0.9241 - loss:
0.2187▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯ 388/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 780us/step - accuracy:
0.9234 - loss: 0.2206▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.9229 - loss: 0.2222▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 777us/step - accuracy: 0.9225 - loss: 0.2232▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.9223 - loss: 0.2238▯▯▯▯▯▯▯▯
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650/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.9221 - loss:
0.2242▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
▯▯▯▯▯▯▯▯▯▯▯▯▯ 715/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy:
0.9219 - loss: 0.2244▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.9218 - loss: 0.2247▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 777us/step - accuracy: 0.9216 - loss: 0.2251▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9214 - loss: 0.2254▯▯▯▯▯▯▯▯
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970/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 779us/step - accuracy: 0.9213 - loss:
0.2256▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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0.9212 - loss: 0.2257▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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p - accuracy: 0.9211 - loss: 0.2257▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━ 0s 777us/step - accuracy: 0.9210 - loss: 0.2257▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯▯
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━━━━━━━━━━━━━━━ 0s 777us/step - accuracy: 0.9209 - loss: 0.2258▯▯▯▯▯▯▯▯
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297/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.9209 - loss:
0.2258□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9209 - loss: 0.2258□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9209 - loss: 0.2257□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 776us/step - accuracy: 0.9209 - loss: 0.2257□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.9208 - loss: 0.2257□□□□□□□□
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626/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy: 0.9208 - loss:
0.2257□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9208 - loss: 0.2257□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9208 - loss: 0.2257 - val_accuracy: 0.8794 - val_loss:
0.3451
Epoch 30/30
   1/1719 ━━━━━━━━━━━━━━━━━━━━ 19s 11ms/step - accuracy: 0.9688 - loss:
0.1983□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.9391 - loss: 0.1896□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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p - accuracy: 0.9324 - loss: 0.2011□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 1s 785us/step - accuracy: 0.9290 - loss: 0.2088□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 1s 781us/step - accuracy: 0.9272 - loss: 0.2124□□□□□□□□
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324/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 779us/step - accuracy: 0.9260 - loss:
0.2145□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 390/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 776us/step - accuracy:
0.9252 - loss: 0.2165□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 454/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 777us/ste
p - accuracy: 0.9246 - loss: 0.2180□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 778us/step - accuracy: 0.9242 - loss: 0.2190□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 778us/step - accuracy: 0.9239 - loss: 0.2196□□□□□□□□
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650/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 776us/step - accuracy: 0.9237 - loss:
0.2200□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□ 716/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/step - accuracy:
0.9236 - loss: 0.2202□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□□□ 781/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 775us/ste
p - accuracy: 0.9234 - loss: 0.2206□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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━ 0s 773us/step - accuracy: 0.9232 - loss: 0.2209□□□□□□□□□□□□□□□□□□□□□
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━━━━━━━━━━━━━━━ 0s 773us/step - accuracy: 0.9231 - loss: 0.2212□□□□□□□□
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982/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy: 0.9229 - loss:
0.2214
1049/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 770us/step - accuracy:
0.9228 - loss: 0.2215
1116/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 769us/ste
p - accuracy: 0.9227 - loss: 0.2215
1182/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 769us/step - accuracy: 0.9226 - loss: 0.2215
1249/1719 ━━━━
━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.9226 - loss: 0.2216
1
316/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy: 0.9225 - loss:
0.2216
1381/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy:
0.9225 - loss: 0.2216
1446/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/ste
p - accuracy: 0.9224 - loss: 0.2216
1512/1719 ━━━━━━━━━━━━━━━━━━━
━ 0s 767us/step - accuracy: 0.9224 - loss: 0.2215
1578/1719 ━━━━
━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.9224 - loss: 0.2215
1
644/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 767us/step - accuracy: 0.9223 - loss:
0.2215
1711/1719 ━━━━━━━━━━━━━━━━━━━━ 0s 766us/step - accuracy:
0.9223 - loss: 0.2215
1719/1719 ━━━━━━━━━━━━━━━━━━━━ 1s 823us/ste
p - accuracy: 0.9223 - loss: 0.2215 - val_accuracy: 0.8802 - val_loss:
0.3446
```

The model is provided with both a taining set and a validation set. At each step, the model will report its performance on both sets. This will also allow to visualize the accuracy and loss curves on both sets (more later).

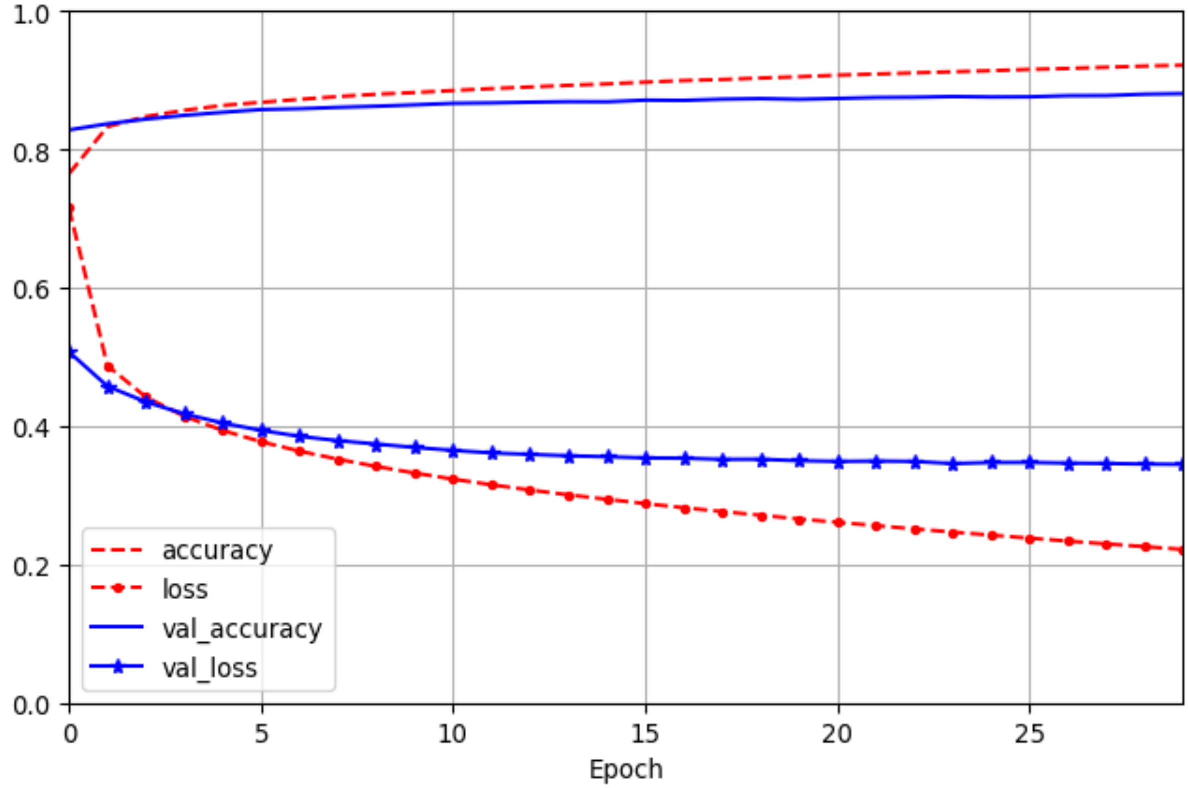
When calling the `fit` method in Keras (or similar frameworks), each step corresponds to the evaluation of a mini-batch. A mini-batch is a subset of the training data, and during each step, the model updates its weights based on the error calculated from this mini-batch.

An epoch is defined as one complete pass through the entire training dataset. During an epoch, the model processes multiple mini-batches until it has seen all the training data once. This process is repeated for a specified number of epochs to optimize the model's performance.

Visualization

In [30]:
```python
import pandas as pd
```

```
pd.DataFrame(history.history).plot(
    figsize=(8, 5), xlim=[0, 29], ylim=[0, 1], grid=True, xlabel="Epoc
    style=["r--", "r--.", "b-", "b-*"])
plt.legend(loc="lower left")  # extra code
plt.show()
```



Evaluating the Model on our Test Set

In [31]:
```
model.evaluate(X_test, y_test)
```

```
  1/313 ━━━━━━━━━━━━━━━━━━━━ 3s 10ms/step - accuracy: 0.8750 - loss: 0.
5036□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□107/313 ━━━━━━━━━━━━━━━━━━━━ 0s 473us/step - accuracy: 0.8797 -
loss: 0.3516□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
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0.8743 - loss: 0.3643□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□□□□□□□□□□□□□□□□□□□□□□□□313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 483us/step -
accuracy: 0.8740 - loss: 0.3650
[0.3627529740333557, 0.8744999766349792]
```

Making Predictions

In [32]:
```
X_new = X_test[:3]
y_proba = model.predict(X_new)
y_proba.round(2)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□□
□□□1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 28ms/step
array([[0.  , 0.  , 0.  , 0.  , 0.  , 0.19, 0.  , 0.01, 0.  , 0.81],
       [0.  , 0.  , 1.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ],
       [0.  , 1.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  , 0.  ]],
      dtype=float32)
```

...

In [33]:
```
y_pred = y_proba.argmax(axis=-1)
y_pred
```

```
array([9, 2, 1])
```

...

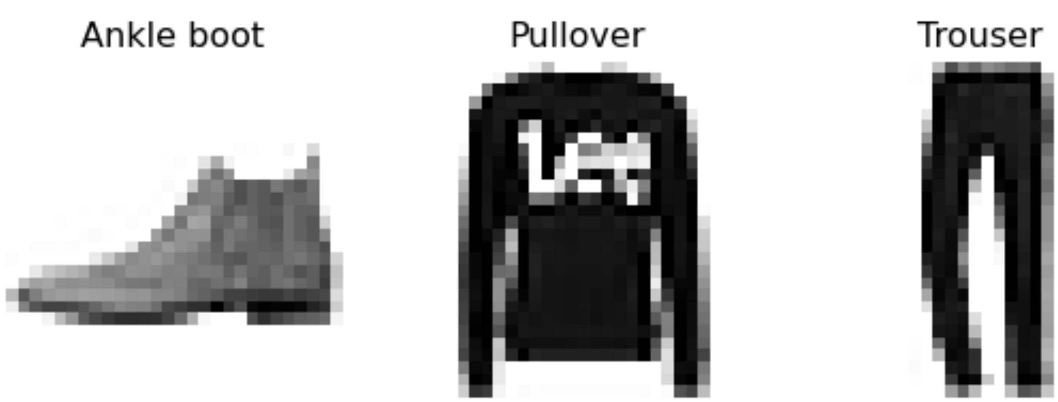
In [34]:
```
y_new = y_test[:3]
y_new
```

```
array([9, 2, 1], dtype=uint8)
```

As can be seen, the predictions are unambiguous, with only one class per prediction exhibiting a high value.

Predicted vs Observed

In [35]:
```
plt.figure(figsize=(7.2, 2.4))
for index, image in enumerate(X_new):
    plt.subplot(1, 3, index + 1)
    plt.imshow(image, cmap="binary", interpolation="nearest")
    plt.axis('off')
    plt.title(class_names[y_test[index]])
plt.subplots_adjust(wspace=0.2, hspace=0.5)
plt.show()
```



In [36]:
```
np.array(class_names)[y_pred]
```

```
array(['Ankle boot', 'Pullover', 'Trouser'], dtype='<U11')
```

Test Set Performance

In [37]:
```
from sklearn.metrics import classification_report

y_proba = model.predict(X_test)
y_pred = y_proba.argmax(axis=-1)
```

Test Set Performance

In [38]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.86      0.80      0.83      1000
           1       0.99      0.97      0.98      1000
           2       0.76      0.84      0.80      1000
           3       0.79      0.94      0.86      1000
           4       0.82      0.78      0.80      1000
           5       0.90      0.98      0.94      1000
           6       0.76      0.63      0.69      1000
           7       0.94      0.92      0.93      1000
           8       0.96      0.96      0.96      1000
           9       0.98      0.92      0.95      1000

    accuracy                           0.87     10000
   macro avg       0.88      0.87      0.87     10000
weighted avg       0.88      0.87      0.87     10000
```

Prologue

Summary

- **Neural Networks Foundations:**
  We introduced bio-inspired computation with neurodes and threshold logic units, outlining the perceptron model and its limitations (e.g., the XOR problem).

- **From Perceptrons to Deep Networks:**
  We explained the evolution to multilayer perceptrons (MLPs) and feedforward architectures, emphasizing the critical role of nonlinear activation functions (sigmoid, tanh, ReLU) in enabling gradient-based learning and complex function approximation.

- **Universal Approximation:**
  We discussed how even single hidden layer networks can approximate any

continuous function on a compact set, highlighting the theoretical underpinning of deep learning.

- **Practical Frameworks and Applications:**
  Finally, we reviews leading deep learning frameworks (PyTorch, TensorFlow, Keras) and demonstrates practical model-building using the Fashion-MNIST dataset, covering model training, evaluation, and prediction.

3Blue1Brown on Deep Learning

- But what is a Neural Network?
  - youtu.be/aircAruvnKk
  - 19 minutes
- Gradient descent, how neural networks learn?
  - youtu.be/IHZwWFHWa-w
  - 21 minutes
- What is backpropagation really doing?
  - youtu.be/Ilg3gGewQ5U
  - 14 minutes
- Backpropagation calculus
  - youtu.be/Ilg3gGewQ5U
  - 10 minutes

Next lecture

- Training Deep Learning Models

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