From Pixels to Predictions: Building a Deep Learning Model

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Introduction

THE CHALLENGE: BUILDING A MACHINE LEARNING MODEL TO INTERPRET AND CLASSIFY VISUAL DATA.

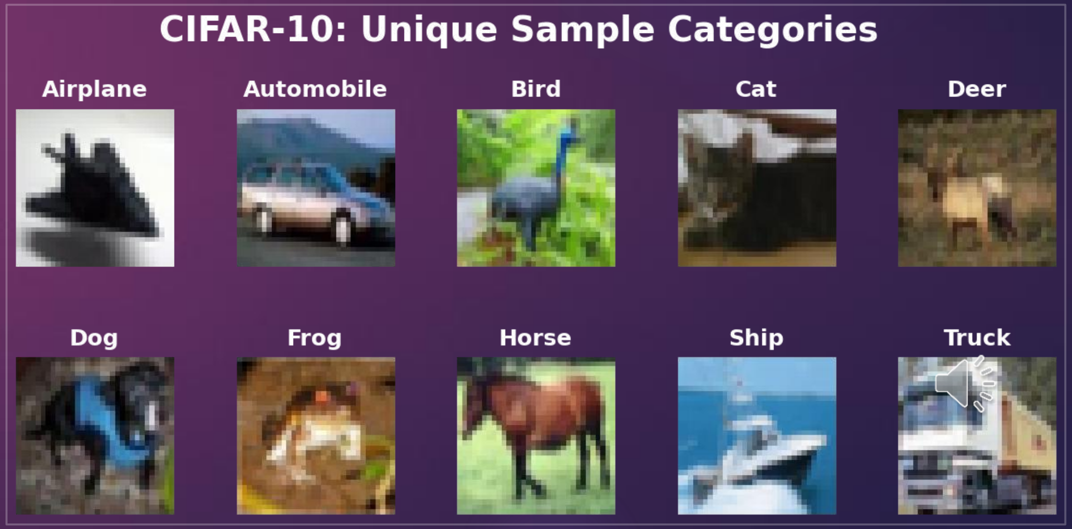
THE PROCESS: DESIGNING AND FINE-TUNING NEURAL NETWORKS TO BALANCE SIMPLICITY AND PERFORMANCE.

THE JOURNEY: TACKLING TECHNICAL CHALLENGES AND UNCOVERING INSIGHTS INTO THE POWER AND LIMITATIONS OF NEURAL NETWORKS.

(LeCun, Bengio, and Hinton, 2015)

CIFAR-10

- **60,000 images spanning 10 categories** : 50,000 allocated for training purposes and 10,000 reserved for testing.
- **Challenge :** Identifying patterns in images sized at 32x32 pixels.
- **Complexity :** Distinguishing between visually similar classes presents a significant challenge.
- **Versatility :** Perfect for feature extraction, augmentation, and the evaluation of models.



(Krizhevsky and Hinton, 2009, pp. 5–6)

Framework

Framework	Advantages	Disadvantages
Keras	Simple, beginner-friendly, fast prototyping	Limited flexibility for complex use cases
PyTorch	Flexible, dynamic computation graph, great for research	Steeper learning curve, less deployment focus
TensorFlow + Keras	Combines simplicity with scalability, production-ready tools	More complex than Keras alone, steeper learning curve

(Medavarapu, 2024; Dai et al., 2022; Wang et al., 2024)

Network Architecture

- **First Layer:** Extracts basic visual features (edges, textures).
- **Second Layer:** Captures more detailed patterns, such as shapes and contours.

```
# First convolutional layer
model.add(Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 32, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2))

# Second convolutional layer
model.add(Conv2D(64, (3, 3), activation='relu', padding='same', kernel_constraint=MaxNorm(3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

(Srivastava et al., 2014; Brownlee, 2019)

Network Architecture

- Third Layer: Focuses on high-level abstractions and class differentiation.
- Dense Layer: Combines features for final decisions, followed by a softmax output for 10-class probabilities.

```
# Third convolutional layer
model.add(Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.3))

# Flatten the output for the dense layers
model.add(Flatten())

# Fully connected dense layer
model.add(Dense(256, activation='relu', kernel_constraint=MaxNorm(3)))
model.add(Dropout(0.5))

# Output layer
model.add(Dense(10, activation='softmax'))
```

(Krizhevsky, Sutskever, and Hinton, 2012; Srivastava et al., 2014; Murugan, 2018)

Activation and Loss Functions

ReLU:

- Tackles the vanishing gradient problem.
- Outputs zero for negatives, scales positives linearly.

Softmax:

- Converts outputs into probabilities.
- Perfect for multi-class classification.

Categorical Cross-Entropy:

- Minimises prediction errors.

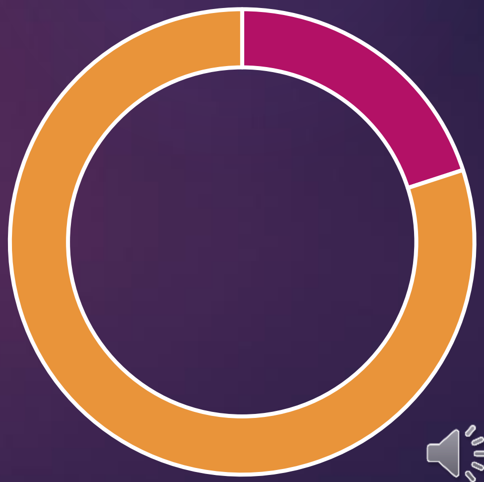
(Asadi and Jiang, 2020; Franke and Degen, 2023; Mao, Mohri, and Zhong, 2023)

Data Partitioning

- **80-20 Split**: Balanced, efficient, and dependable
- **90-10 Split**: Tested but caused instability and overfitting.
- **K-Fold Cross-Validation**: Improved generalisation but required excessive resources.

Final Decision: 80-20 split for its stability and practicality.

Data Partitioning



(Hebart and Vicente, 2016; Xu and Goodacre, 2018)

Preprocessing

Normalisation: Scaled pixel values to 0.0–1.0 for consistent input and faster convergence.

(Huang et al., 2020)

One-Hot Encoding: Converted class labels for compatibility with categorical cross-entropy.

(Mao, Mohri, and Zhong, 2023)

Data Augmentation: Added random rotations, shifts, and flips to enhance generalisation.

(Shorten and Khoshgoftaar, 2019)

Training Process

Initial Setup: 25 epochs, learning rate of 0.1, batch size of 32.

First Adjustment: Increased to 50 epochs, but early stopping triggered at 30. Adjusted learning rate to 0.01 with decay.

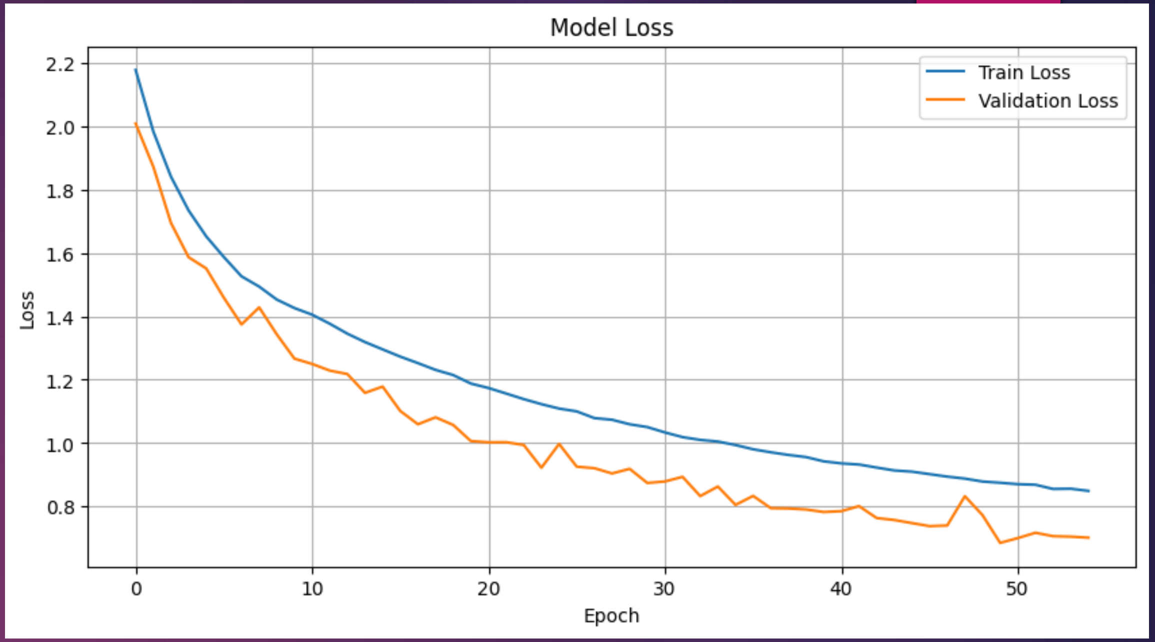
Second Adjustment: Extended to 75 epochs; early stopping occurred at 55 and later at 66 epochs.

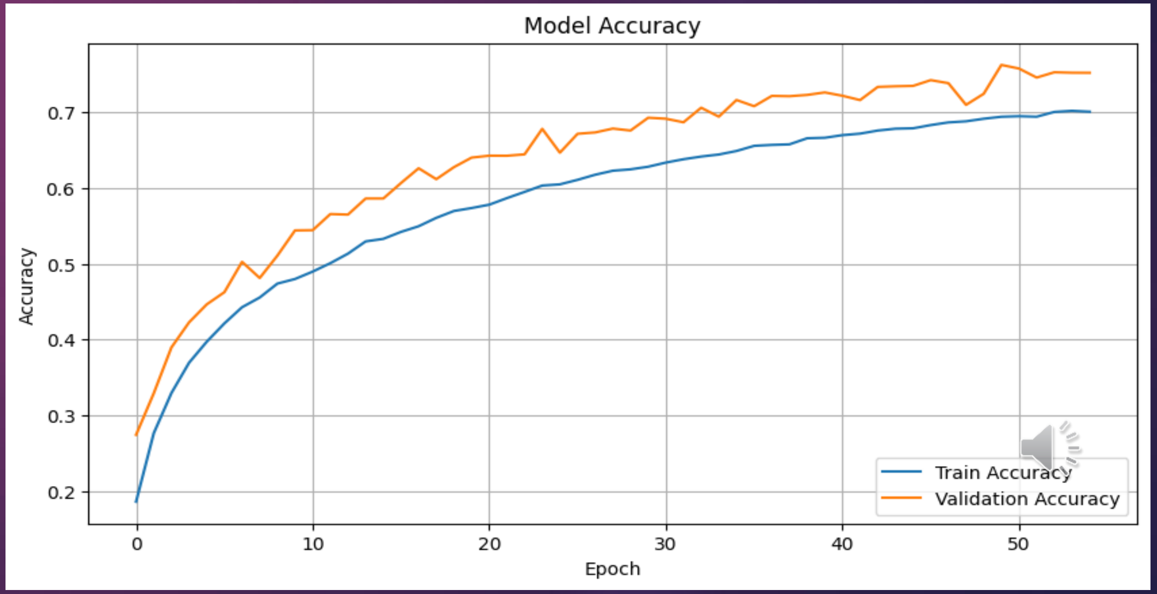
Outcome: Careful parameter tuning ensured stability, efficiency, and effective learning.

(Granziol, Zohren, and Roberts, 2022; Ji, Li, and Telgarsky, 2021; Smith, 2017)

Validation Strategy

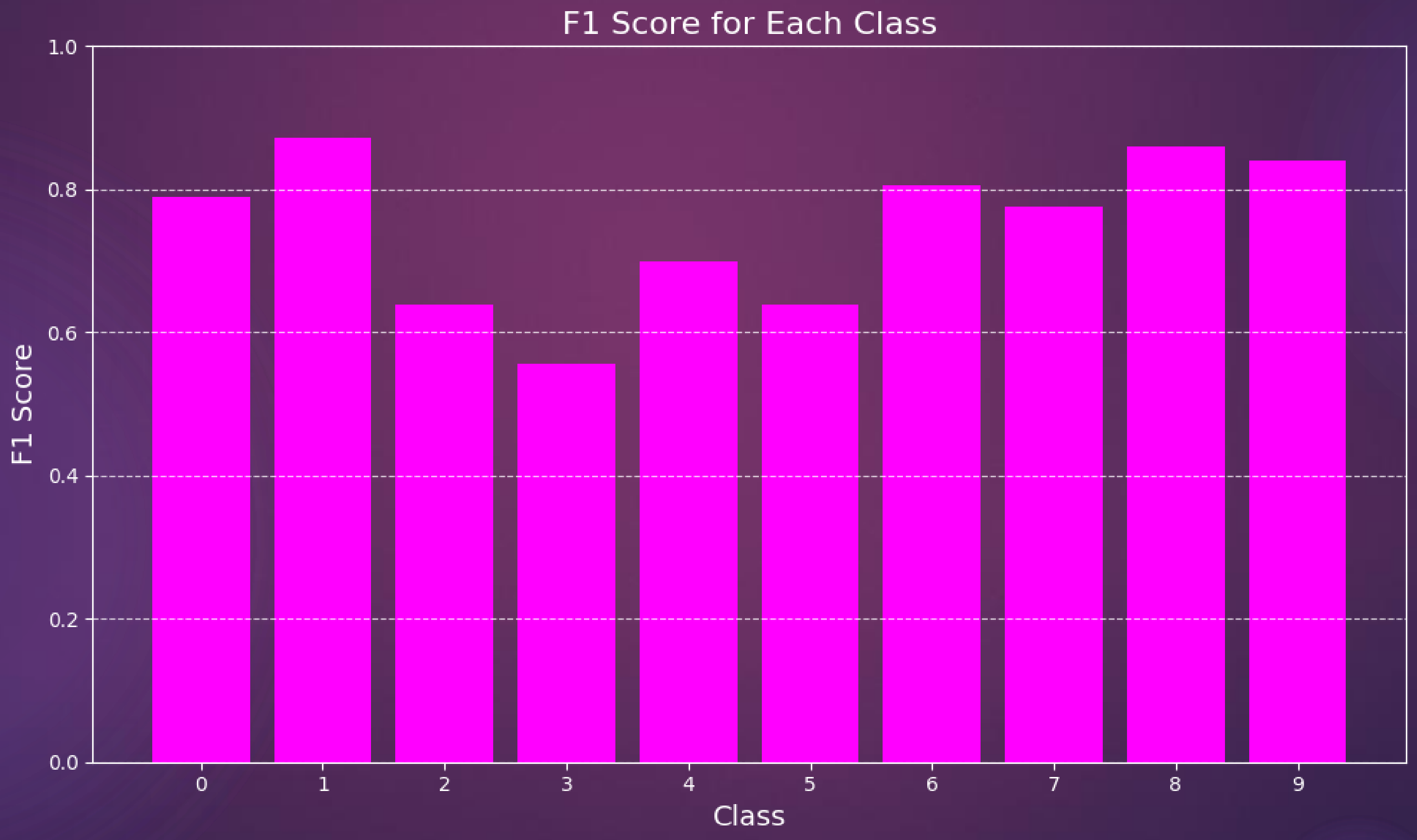
- Tracked validation accuracy and loss metrics following each epoch.
- Implemented early stopping to avoid overfitting and conserve resources.
- Retrieved the best weights to ensure optimal performance and strong generalisation.





(Mahsereci et al., 2017; Vilares Ferro et al., 2024)

Testing and Results



(Ahmadian et al., 2024; Bénédict et al., 2021; Tsoi et al., 2020)

Critical Analysis

Class Imbalances:

Precision and recall varied across classes, highlighting a need for targeted data collection or augmentation.

Overfitting:

Validation loss fluctuations suggest room for stronger regularisation.

Simple Architecture:

Deeper networks or pre-trained models could improve complex pattern recognition.

(Buda et al., 2018; Srivastava et al., 2014; He et al., 2016)

Reflections: Key Lessons and Growth

- Straightforward methods outperformed complex ones.
- Debugging required attention to detail.
- Early stopping and data augmentation improved optimization.
- Theory combined with practice enhanced learning.
- Resilience and adaptability drove progress

(Bergman et al., 2024; Schneider et al., 2021)

Bridging Theory and Real-World Impact

- Precision and recall inform critical systems.
- Data augmentation improves model performance in diverse conditions.
- Builds a foundation for scalable, adaptive AI solutions to tackle real-world challenges

(Chen et al., 2024; Tong et al., 2023)

Conclusion

This project was not just about achieving 75.62% accuracy—it was a journey of creativity, growth, and problem-solving. Challenges became lessons, paving the way for exploring even greater possibilities in deep learning.

This is just the beginning of the adventure! 🚀

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