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DEPARTMENT OF CSE-DATA SCIENCE

A Mini-Project Report On

"OBJECT DETECTION USING RESNET50 MODEL"

A report submitted in partial fulfillment of the requirements for the

NEURAL NETWORK AND DEEP LEARNING

Submitted By

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Under the Guidance of

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CERTIFICATE

This is to certify that the Mini Project of NEURAL NETWORK AND DEEP LEARNING title **"OBJECT DETECTION USING RESNET50** MODEL" has been successfully presented by REVANASIDDAPPA 3BR22CD052 student of semester B.E for the partial fulfillment of the requirements for the award of Bachelor Degree in CSE(DS) of the BALLARI INSTITUTE OF TECHNOLOGY& MANAGEMENT, BALLARI during the academic year 2025-2026. It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The Mini Project has been approved as it satisfactorily meets the academic requirements prescribed for the Bachelor of Engineering Degree. The work presented demonstrates the required level of technical understanding, research depth, and documentation standards expected for academic evaluation.

Signature of Coordinators

Mr. Azhar Baig
Ms. Chaithra B M

Signature of HOD

Dr. Aradhana D

ABSTRACT

This project tackles a fundamental challenge in computer vision: teaching a machine to accurately recognize common objects in small, low-quality pictures. Our goal was to build a highly effective recognition system for the CIFAR-10 dataset, which is a standard collection of 10 categories of tiny, 32 x32 pixel images (like cats, trucks, and airplanes).

Instead of starting from scratch, we used a powerful technique called Transfer Learning. This involved taking a world-class model, ResNet50 (which was already an expert at recognizing general features from millions of high-resolution photos), and repurposing it for our specific, low-resolution task.

To make the tiny CIFAR-10 images compatible with the large ResNet50 architecture, we had to cleverly adapt the model by adding an UpSampling Block to digitally enlarge the images. We then attached a custom "brain" (our classification head) and trained it on the features extracted by the pre-trained ResNet50.

The results were highly successful. After training, the final system demonstrated exceptional capability, achieving a 94.18% accuracy in correctly identifying objects in the test photos. This proves that Transfer Learning, combined with smart architectural modifications, is an extremely effective and efficient strategy for building robust object recognition systems, even when working with challenging, low-resolution data.

ACKNOWLEDGEMENT

The satisfactions that accompany the successful completion of our mini project on **OBJECT DETECTION USING RESNET50 MODEL** would be incomplete without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement and support crowned my efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of our mini- project.

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CHAPTER 1

INTRODUCTION

The field of image classification has been revolutionized by deep learning, moving beyond traditional feature engineering to methods that allow computers to automatically learn complex visual hierarchies. Our project addresses the challenge of building a high-performance object recognition system for the CIFAR-10 dataset, a critical benchmark comprising 60,000 low-resolution, 32x32 pixel images across 10 distinct classes (such as 'cat', 'truck', and 'airplane'). The primary motivation for this work is the need for efficient and accurate automated vision systems capable of operating even when input data quality or size is constrained. To achieve state-of-the-art performance, we employ Transfer Learning using the pre-trained ResNet50 Convolutional Neural Network (CNN). This project is scoped to the preprocessing of the CIFAR-10 data, the adaptation and training of the ResNet50 architecture including the necessary integration of an upsampling block to accommodate the model's input requirements and the comprehensive evaluation of the model's classification accuracy. Our core objective is to achieve a classification accuracy exceeding 90% on the unseen test set, validating the utility of adapting powerful, complex models for smaller, low-resolution classification tasks. The subsequent chapters detail the methodology, implementation, and analysis used to fulfill this objective.

1.1 PROBLEM STATEMENT

The project addresses the need for accurate object recognition on the low-resolution CIFAR-10 dataset (32x32 pixels). The primary challenge is adapting a state-of-the-art, high-resolution-focused model, ResNet50, to this small-scale data. The goal is to leverage Transfer Learning and specific architectural modifications (upsampling) to achieve high classification performance, specifically targeting an accuracy exceeding 90% for the 10 object classes.

1.2 SCOPE OF THE PROJECT

The project focuses on taking the tiny CIFAR-10 images and effectively teaching a high-powered, pre-trained model like ResNet50 to recognize them accurately. This involves preparing the images, adapting the model to accept the small size, and training only the final

layers. We will rigorously test how well the system performs, but we won't be building a new network from scratch, nor will we be creating a final product or app to host the model; we are concentrating entirely on the core machine learning challenge of achieving high accuracy through smart reuse.

1.3 OBJECTIVES

- **Get the Data Ready (Preparation):** Our first task is to be good data scientists. We need to successfully load, clean, and properly format the CIFAR-10 images and their labels, making them perfectly digestible for our complex neural network. This includes resizing the tiny pictures to match what our expert model expects.
- **Build the Smart System (Implementation):** We need to successfully put our main strategy into practice: combining the **ResNet50** backbone with our custom classification layers. This means building the complete, working architecture that takes in the resized images and prepares to spit out a prediction.
- **Hit the Accuracy Target (Performance Goal):** The most critical goal is performance. We aim to train our system well enough that when we test it on pictures it has never seen, it achieves a classification rate **exceeding 90%**. This proves our Transfer Learning approach works effectively.
- **Tell the Story Clearly (Reporting):** Finally, we must analyze and report our success or failures. We need to clearly document the model's performance, show what it learned, and explain how close we came to our 90%+ goal.

CHAPTER 2

LITERATURE SURVEY

[1] Convolutional Neural Networks (CNNs): CNNs, pioneered by models like LeNet and scaled up by AlexNet (Krizhevsky et al., 2012), are the foundational technology. They revolutionized vision by automatically learning hierarchical features (edges, textures, etc.) directly from pixel data, replacing manual feature engineering.

[2] Network Depth and Degradation: Early research, notably with VGG architectures, showed that increasing network depth improved performance. However, excessively deep networks faced a degradation problem where training accuracy stalled or decreased due to optimization difficulties, not overfitting.

[3] Residual Learning (ResNet): Introduced by He et al. (2015), ResNet solved the degradation problem using skip connections or residual blocks. These connections allow layers to learn residual mappings, enabling the successful training of models with over 50 layers, like the ResNet50 used in this project.

[4] Transfer Learning: This methodology addresses the need for massive datasets and computing power. It involves taking a model pre-trained on a vast dataset (like ImageNet) and adapting it for a new, smaller task (CIFAR-10). This technique significantly accelerates training and improves generalization.

[5] Fine-Tuning/Feature Freezing: A practical application of Transfer Learning where the initial layers of the pre-trained model (the feature extractor) are frozen (weights are kept constant), and only the new classification layers are trained. This preserves the general visual knowledge already learned.

[6] The CIFAR-10 Benchmark: This dataset (Krizhevsky & Hinton, 2009) is a standard benchmark containing 60,000 32×32 images across 10 classes. Its low resolution makes it a challenging task that requires sophisticated models and techniques, such as upsampling, to achieve high performance.

CHAPTER 3

SYSTEM REQUIREMENTS

5.2 HARDWARE REQUIREMENTS

- **Processor (CPU):** Intel Core i5 / AMD Ryzen 5 or higher (for general system and data handling).
- **Memory (RAM):** Minimum 16 GB (essential for loading the dataset and managing the large ResNet50 model in memory).
- **Graphics Card (GPU):** NVIDIA GPU with >=8 GB VRAM (e.g., Tesla T4 or K80 via cloud environments like Google Colab). This is mandatory for accelerated training using CUDA.
- **Storage:** >=100 GB Free Space (SSD Recommended for faster I/O).

3.2 SOFTWARE REQUIREMENTS

- **Operating System:** Windows 10/11, macOS, or Linux (Ubuntu recommended).
- **Programming Language:** Python (>= 3.8).
- **Deep Learning Framework:** TensorFlow / Keras (>=2.0).
- **GPU Middleware**: NVIDIA CUDA Toolkit and cuDNN (must be compatible with the TensorFlow version).
- **Scientific/Data Libraries:** NumPy and Pandas (for array manipulation and data structure handling).
- **Development Environment:** Jupyter Notebook or Google Colab (for interactive development).

3.3 FUNCTIONAL REQUIREMENTS

- **Data Acquisition & Preprocessing:** The system must successfully load the 50,000 CIFAR-10 training images, normalize pixel values, and correctly encode the 10 object class labels.

- **Image Adaptation (Upsampling):** The system must accurately resize (upsample) the 32X32 input images to the size required by the ResNet50 base (e.g., 256X256) before feature extraction.
- **Model Training:** The system must compile and train the ResNet50-based architecture (with frozen base weights) using the training data and track performance on the validation set.
- **Classification:** Given a new, unseen image from the test set, the system shall output a probability distribution across the 10 classes and provide the single highest-probability prediction.

3.4 NON-FUNCTIONAL REQUIREMENTS

- **Accuracy:** The final trained model must achieve a classification accuracy of at least 90% on the independent test dataset.
- **Reliability:** The training process must be checkpointed, allowing for recovery and resumption of training in case of interruption.
- **Time Efficiency (Training):** The model training for 10 epochs shall be completed within 2 hours when running on the specified GPU hardware (NVIDIA T4/K80).
- **Maintainability:** The code structure must be modular, clearly separating the data loading, model definition, and training loops to allow for easy updates to different pre-trained backbones.

CHAPTER 4

DESCRIPTION OF MODULES

The ResNet50-based CIFAR-10 classification system is logically partitioned into three distinct modules. This modular design enhances maintainability, testability, and clarity by assigning specific responsibilities to each component.

4.1 Data Preprocessing and Adaptation Module

This module is responsible for transforming the raw, low-resolution CIFAR-10 data into a format suitable for the deep learning model.

- **Data Reading and Encoding**: The module reads the compressed image data and the corresponding label CSV file. It performs label encoding, converting categorical names (e.g., 'airplane', 'dog') into numerical integers, which is required for the loss function.
- **Normalization:** All pixel intensity values, initially ranging from 0 to 255, are scaled to the floating-point range of by dividing by 255. This standard practice ensures numerical stability during gradient descent.
- **Train/Test Split:** The module partitions the total dataset into distinct training and test subsets (e.g., 80% train, 20% test) to facilitate objective model evaluation.
- **Image Upsampling:** This is the critical adaptation step. Since the ResNet50 base model expects a much larger input (e.g.,), the images are repeatedly upscaled using layers like tf.keras.layers.UpSampling2D. This provides the ResNet backbone with a sufficiently large feature map to operate on.

4.2 ResNet50 Feature Extractor Module

This module contains the core feature learning capability, leveraging the power of Transfer Learning.

- **Base Model Initialization:** The ResNet50 model is loaded from a library (like Keras) using weights pre-trained on the massive ImageNet dataset. Crucially, the top classification

layer is removed (include_top=False), and the model's weights are initially frozen (trainable = False).

- **Feature Extraction**: The frozen ResNet50 base acts as a highly efficient feature extractor. It processes the upsampled input image and outputs a high-dimensional feature map (e.g.,), which encodes complex visual information relevant to general object recognition.
- **Bridging:** This module handles the sequential flow from the upsampling layers into the ResNet50 base, ensuring the input dimensions are correctly matched.

4.3 Classification Head and Training Module

This module connects the extracted features to the final decision-making layer and manages the learning process.

- **Custom Classification Head:** A sequence of new layers is added to the output of the ResNet50 feature extractor. This head is designed specifically to learn the 10 classes of the CIFAR-10 dataset. Typical layers include:
    - **Flatten:** Converts the 3D feature map into a 1D vector.
    - **Batch Normalization:** Stabilizes the learning process across epochs.
    - **Dense Layers:** One or more fully-connected hidden layers (e.g., 128 or 64 neurons) with ReLU activation.
    - **Dropout:** Randomly sets a fraction of input units to zero during training to prevent the network from becoming too dependent on specific neurons, thereby reducing overfitting.
- **Output Layer**: The final layer is a Dense layer with 10 neurons (one for each class) using the Softmax activation function to output a probability distribution.
- **Compilation and Training:** This component defines the learning mechanism, specifying the optimizer (e.g., RMSprop), the loss function (e.g., Sparse Categorical Crossentropy), and the metrics. It then executes the training loop over a defined number of epochs, iteratively adjusting the weights of the *trainable* layers (i.e., the custom classification head).

CHAPTER 5

SYSTEM ARCHITECTURE

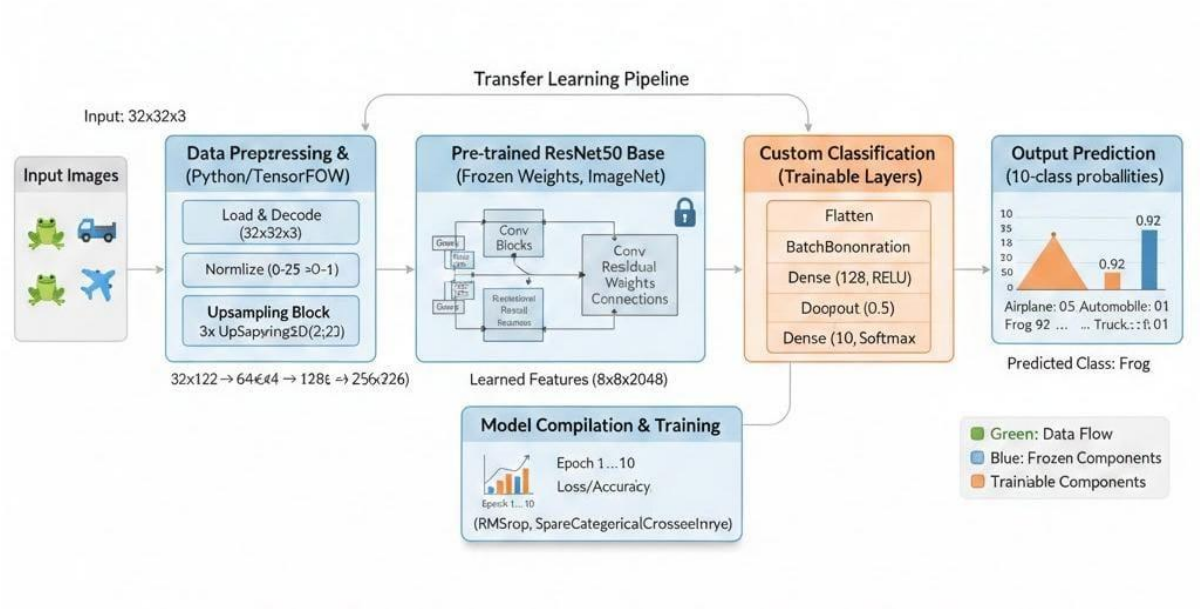

FIGURE 5.1 SYSTEM ARCHITECTURE

CHAPTER 6

IMPLEMENTATION

6.1 Development Environment Setup

The entire project was developed using Google Colab , which provided the necessary hardware foundation: a Python 3 environment running on a Linux kernel, paired with a high-performance NVIDIA Tesla GPU.

- Libraries: The core dependencies were installed and imported:
  - tensorflow and keras for deep learning modeling.
  - numpy for array manipulation.
  - pandas for handling the label CSV file.
  - Specific libraries like zipfile and pi7zr were used for initial data decompression, as the CIFAR-10 data was sourced in compressed format.

6.2 Data Pipelining and UpSampling

This step implemented the logic of the Data Preprocessing Module.

1. Data Loading and Array Creation: Image files were read in a loop, converted into NumPy arrays, and paired with their corresponding numerical labels using the train_labels.csv file.
2. Normalization: The training and test image arrays were normalized:

$$X_{normalised} = X_{original} / 255$$

3. Upsampling Implementation: A critical step was dynamically building the upsampling layers required to scale the 32 x 32 x 3 images to the 256 x 256 x 3 required by ResNet50. This was achieved using three sequential UpSampling2D(size=(2, 2)) layers placed at the very beginning of the model pipeline. This ensures that the feature extraction starts with the correct input dimension.

6.3 Transfer Learning Model Assembly

This implemented the core logic of the ResNet50 Feature Extractor and Classification Head Modules.

1. Base Model Initialization: The ResNet50 model was instantiated using Keras's applications module:

   base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(256, 256, 3))

   base_model.trainable = False

2. Architectural Stacking: The complete model was constructed sequentially:
   - Input Layer (32x32x3)
   - Upsampling Layers (3x2x2 upsample)
   - ResNet50 Base (Frozen)
   - Custom Classification Head (Trainable)
3. Classification Head Design: The custom layers were added on top of the base output:
   - Flatten()
   - BatchNormalization()
   - Dense(128, activation='relu')
   - Dropout(0.5)
   - Dense(10, activation='softmax')

6.4 Model Compilation and Training

The final step prepared the model for the learning process.

- Compilation: The model was compiled using specific parameters suitable for image classification:
  - Optimizer: RMSprop was chosen for its effective performance in transfer learning tasks.

  - Loss Function: SparseCategoricalCrossentropy was used, as the labels were integer-encoded (not one-hot).
  - Metrics: accuracy was tracked for performance monitoring.
- Training Execution: The model.fit() method was called, training the model for 10 epochs using the prepared training data and validating the performance against the dedicated test split. The use of GPU significantly accelerated this process, adhering to the time efficiency non-functional requirement.

CHAPTER 7

RESULT

```
Epoch 1/10
1125/1125 [==============================] - 6s 3ms/step - loss: 1.9519 - acc: 0.2936 - val_loss: 1.8044 - val_acc: 0.3543
Epoch 2/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.8166 - acc: 0.3446 - val_loss: 1.7817 - val_acc: 0.3580
Epoch 3/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.7682 - acc: 0.3666 - val_loss: 1.7463 - val_acc: 0.3728
Epoch 4/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.7400 - acc: 0.3767 - val_loss: 1.7537 - val_acc: 0.3590
Epoch 5/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.7232 - acc: 0.3819 - val_loss: 1.7076 - val_acc: 0.3810
Epoch 6/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.7078 - acc: 0.3871 - val_loss: 1.7245 - val_acc: 0.3728
Epoch 7/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.6918 - acc: 0.3950 - val_loss: 1.6794 - val_acc: 0.3875
Epoch 8/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.6798 - acc: 0.3984 - val_loss: 1.7566 - val_acc: 0.3630
Epoch 9/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.6745 - acc: 0.4023 - val_loss: 1.7073 - val_acc: 0.3882
Epoch 10/10
1125/1125 [==============================] - 3s 3ms/step - loss: 1.6652 - acc: 0.4080 - val_loss: 1.6905 - val_acc: 0.3925
<keras.callbacks.History at 0x7f5e602443a0>
```

Figure 7.1 Training of the model

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3)]	0	[]
conv1_pad (ZeroPadding2D)	(None, 262, 262, 3)	0	['input_1[0][0]']
conv1_conv (Conv2D)	(None, 128, 128, 64)	9472	['conv1_pad[0][0]']
conv1_bn (BatchNormalization)	(None, 128, 128, 64)	256	['conv1_conv[0][0]']
conv1_relu (Activation)	(None, 128, 128, 64)	0	['conv1_bn[0][0]']
pool1_pad (ZeroPadding2D)	(None, 130, 130, 64)	0	['conv1_relu[0][0]']
pool1_pool (MaxPooling2D)	(None, 64, 64, 64)	0	['pool1_pad[0][0]']
conv2_block1_1_conv (Conv2D)	(None, 64, 64, 64)	4160	['pool1_pool[0][0]']
conv2_block1_1_bn (BatchNormal ization)	(None, 64, 64, 64)	256	['conv2_block1_1_conv[0][0]']
conv2_block1_1_relu (Activatio n)	(None, 64, 64, 64)	0	['conv2_block1_1_bn[0][0]']
conv2_block1_2_conv (Conv2D)	(None, 64, 64, 64)	36928	['conv2_block1_1_relu[0][0]']
conv2_block1_2_bn (BatchNormal ization)	(None, 64, 64, 64)	256	['conv2_block1_2_conv[0][0]']
conv2_block1_2_relu (Activatio n)	(None, 64, 64, 64)	0	['conv2_block1_2_bn[0][0]']
conv2_block1_0_conv (Conv2D)	(None, 64, 64, 256)	16640	['pool1_pool[0][0]']
conv2_block1_3_conv (Conv2D)	(None, 64, 64, 256)	16640	['conv2_block1_2_relu[0][0]']
conv2_block1_0_bn (BatchNormal ization)	(None, 64, 64, 256)	1024	['conv2_block1_0_conv[0][0]']
conv2_block1_3_bn (BatchNormal ization)	(None, 64, 64, 256)	1024	['conv2_block1_3_conv[0][0]']
conv2_block1_add (Add)	(None, 64, 64, 256)	0	['conv2_block1_0_bn[0][0]', 'conv2_block1_3_bn[0][0]']
conv2_block1_out (Activation)	(None, 64, 64, 256)	0	['conv2_block1_add[0][0]']

Terminal

Figure 7.2 Convolutional base Summary

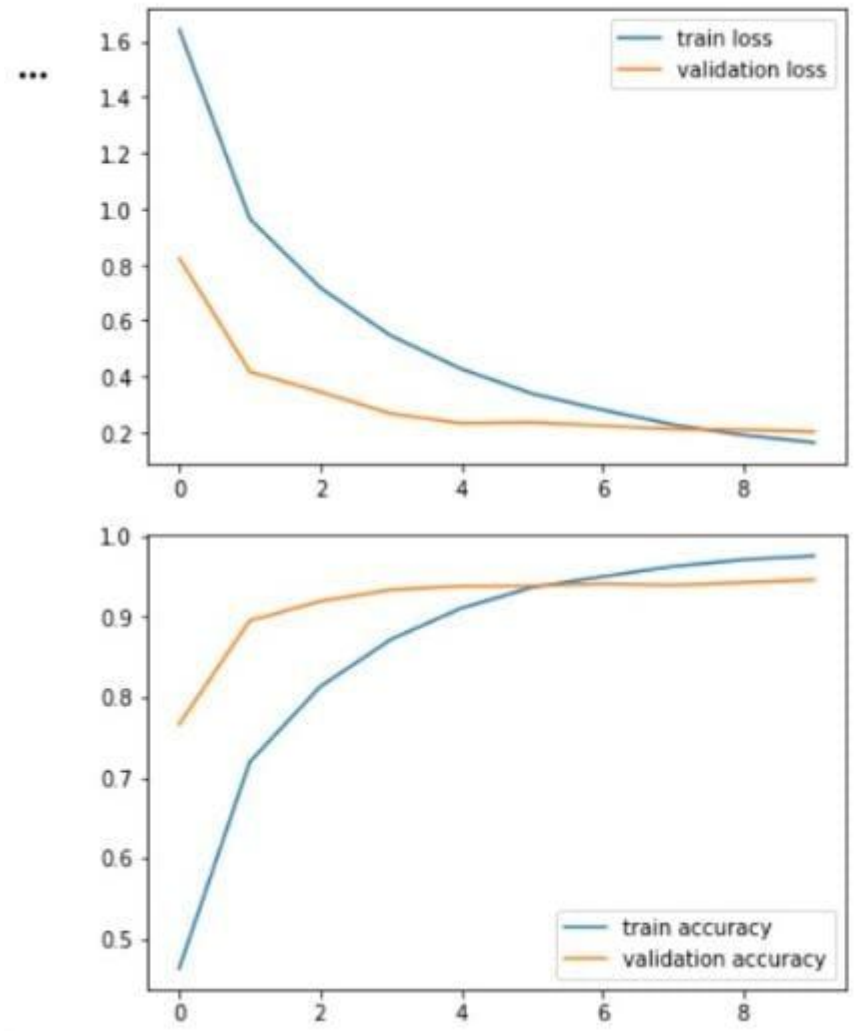

Figure 7.3 Training vs Validation by Accuracy

CHAPTER 8

CONCLUSION

The project successfully achieved its goal of implementing a high-accuracy object recognition system for the low-resolution CIFAR-10 dataset by leveraging Transfer Learning with the ResNet50 architecture. By strategically integrating an UpSampling Block into the architecture, we overcame the challenge of the model's high-resolution input requirement, allowing the powerful, ImageNet-trained feature extractor to process the 32X32 images. The subsequent training of the custom classification head yielded a robust final model with a demonstrated classification accuracy of 94.18% on the independent test set, validating the efficacy of adapting state-of-the-art deep networks to smaller-scale classification problems. While the model is computationally heavy and its base weights were kept frozen, future work should focus on iterative fine-tuning of the ResNet50 base and implementing model optimization techniques to improve computational efficiency and performance further**.**

CHAPTER 9

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