TRAFFIC SIGN DETECTION USING DEEP LEARNING APPROACH

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Project titled "**Traffic Sign Detection Using Deep Learning Approach**", submitted by **Md. Masud Rana Babu, ID No: 241-25-002** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **24-05-2025**.

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We hereby declare that this project has been done by us under the supervision of **Dr. Arif Mahmud Associate Professor and Associate Head, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Traffic sign detection stands as a vital operational aspect of autonomous driving systems while forming an essential part of intelligent transportation technology. Research investigations take a deep learning method to detect traffic signs in images. The collected traffic sign image dataset from Kaggle underwent a precursing process including resizing as well as contrast enhancement and gamma correction and data augmentation. The researcher established three sets for data processing: training with 3,200 images and testing with 400 images alongside validation with 400 images.Analysis of traffic sign recognition capabilities was conducted by evaluating multiple deep learning models namely VGG19 as well as ResNet together with Xception and DenseNet in addition to AlexNet. Xception demonstrated the best accuracy performance at 99% among the evaluated models and AlexNet placed second with 98%, DenseNet achieved 96% accuracy while VGG19 obtained 95% accuracy and ResNet reached a lower mark of 70%. This study establishes modern convolutional neural networks (CNNs) perform traffic sign classification tasks efficiently through which Xception delivered the research's best classification outcomes.Autonomous vehicle navigation and road safety improvements receive significant benefits thanks to deep learning's ability to identify traffic signs precisely during real-time operations. Additional research will concentrate on dataset enlargement along with performance optimization and implementation of the system for practical use.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Overview

Traffic infrastructure relies on essential road signs which provide vital direction to drivers for managing vehicles and protecting safety on the roads. These signs deliver important information about speed restrictions and notice the public of warnings alongside directives for direction and prohibitions. Human drivers sometimes do not detect or read traffic signs because they are distracted by other factors or because of bad weather and limited visibility. Autonomous vehicles need accurate traffic sign perception because this skill is vital for maintaining safe navigation of roads during development.

New technologies from artificial intelligence (AI) combined with deep learning have made traffic sign detection and classification systems more dependable. Image processing displays superior results when operated through Convolutional Neural Networks (CNNs) which perform as specialized deep learning models for image recognition. We construct a high-accuracy traffic sign recognition system through deep learning implementations for various traffic sign classification needs.

Our project works with 4,000 traffic sign images obtained from Kaggle while performing data preprocessing to improve their quality before running different deep learning models to investigate their outcome results. This study evaluates VGG19 and ResNet together with Xception and DenseNet and AlexNet to determine their accuracy rates from 70% to 99%. The main purpose is to select the most effective model from the examined options for use in autonomous driving operations and intelligent transportation systems.

1.2 Background and Present State

Computer vision experienced major progress during the last decade by adopting deep learning as its primary approach to classify images and detect objects while recognizing patterns. These technologies help automated driving systems recognize traffic signs effectively through the application of traffic sign recognition capabilities.

1.2.1 Traditional Approaches: Previous methods of traffic sign detection utilized handcrafted features which included color histograms together with edge detection and shape-based techniques. These methods exhibited significant sensitivity to various environmental factors like lighting changes and physical coverings and image-based disturbances hence their answering capacity and overall stability remained limited.

1.2.2 Modern Deep Learning Approaches: Deep learning has transformed the way traffic signs are recognized during the past couple of years. The CNN models VGG19 and ResNet together with Xception and DenseNet along with AlexNet enable automatic extraction of image high-level features to achieve superior accuracy and resistance over traditional approaches. Large training sets ensure that these models develop advanced pattern recognition abilities which help them identify genuine traffic phenomena across diverse real-life situations.

Despite these advancements, challenges remain:

- It is possible that changing lighting environments diminish the accuracy of recognition systems.
- Sign classification by the model may become less accurate when images have blurring or hiding objects.
- Autonomous vehicles need high computational performance to operate in real-time applications.

Multiple deep learning algorithms receive training on a properly cleaned dataset to establish high recognition accuracy and reliability in traffic signs.

1.3 Problem Statement

Traffic sign misreading creates major road safety problems because it could result in both incidents and traffic offenses. Human operators making manual detections of traffic signs yield errors because their performance is limited by fatigue and distractions as well as environment conditions. The detection of traffic signs in autonomous vehicle systems requires both real-time functionality as well as high accuracy to maintain safety for navigation.

Traffic sign recognition models have experienced recent progress yet they encounter important obstacles during their operation.

- The recognition system demonstrates varied performance depending on diverse weather conditions and picture quality alongside lighting situations.

- The demand for real-time deployment limits deep learning models because of their high computational needs.
- Staff must solve the problem of working with extensive datasets which contain heterogeneous data samples extracted from actual driving circumstances.

The aim of this project involves developing deep learning models to effectively detect traffic signs with high accuracy and efficiency which will lead to better reliability of automated driving sign detection capabilities.

1.4 Objectives

This project uses the following core objectives:

- A dataset consisting of various traffic sign images needs to be gathered along with preprocessing steps for model training through quality inputs.
- The development includes multiple deep learning model training and evaluation of VGG19 and ResNet and Xception and DenseNet and AlexNet for traffic sign recognition tasks.
- To compare the performance of different models in terms of accuracy, computational efficiency, and robustness.
- This research will identify an appropriate model for implementing traffic sign recognition systems.
- This work investigates approaches for enhancing model operational efficiency while enabling real-time processing capabilities in future work.

The project aims to enhance road safety while developing autonomous vehicle perception technology through the successful achievement of its targets.

1.5 Scope and Limitations

Scope of the Project

- The project handles traffic sign classification tasks exclusively whereas detection procedures (locating traffic signs in images) are not part of its scope.
- This method applies image preprocessing operations such as resizing together with contrast enhancement augmentations and gamma correction and image scaling for achieving better model outcomes.

- Several deep learning architectures undergo training assessment to determine the optimal model design.
- The current research utilizes static images from the dataset yet future development aims to examine real-time video signal processing.

Limitations of the Project

- The dataset consists of 4,000 images and it potentially lacks sufficient samples to represent all traffic sign variations globally.
- Research concentrates on established traffic sign types so unknown or fresh sign variants might present difficulties for the model.
- While real-time performance optimization falls outside primary goals the actual deployment requires this aspect to be important.
- The project excludes object detection models because it does not perform simultaneous recognition and classification of signs.

This study presents important findings about deep learning model success in traffic sign recognition yet creates important groundwork for additional research within this domain.

1.6 Report Organization

The report divides into seven sections which examine different project components.

- Chapter 1 Introduction Provides an overview, background, problem statement, objectives, scope, and organization of the report.
- The literature review chapter of this report examines past research about traffic sign recognition by examining classical approaches against deep learning technology.
- The Section of Methodology/Requirement Analysis and Design Specifications provides an explanation of the dataset selection along with preprocessing methods and chosen model types and deployment methodology.
- The chapter outlines how deep learning models get trained along with hyperparameter optimization methods before performing performance evaluations.
- Chapter 5 demonstrates an evaluation of model performance which features a strategic analysis of the most optimal architecture together with its efficiency and accuracy outlooks.

- Traffic sign recognition technology covered in Chapter 6 examines its positive effects on societal well-being and environmental stability and sustainable practices.
- The concluding section combines essential findings with a review of constraints alongside prospective enhancements for upcoming work.

1.7 Summary

The opening segment of this paper explained how the project "Traffic Sign Detection Using Deep Learning Approach" supports both road safety and autonomous driving operations. A deep learning system is being studied to achieve precise traffic sign classification as it handles problems related to misclassification along with varying environmental conditions and computational efficiency concerns.

Traditional traffic sign detection techniques received background discussion followed by an examination of contemporary CNN architectural benefits in VGG19, ResNet, Xception, DenseNet, and AlexNet. The research demanded powerful recognition software alongside objectives to establish a collection system for data points with the goal to assess models and analyze their performance rates. The project maintained its boundaries through well-defined scope and limitations because it only dealt with static image classification instead of real-time detection.

The last portion of this chapter outlined how the report is structured by presenting a summary of the sections included across the chapters. A review of research materials regarding traffic sign recognition along with deep learning strategies will be presented in the following chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The fundamental task in intelligent transportation systems called Traffic Sign Recognition functions critically for enhancing both road safety and autonomous driving systems and driver assistance capabilities. Modern TSR systems benefit from the growing use of artificial intelligence and deep learning technology which permits quick and accurate traffic sign detection regardless of situation.

The second part analyzes existing research studies in traffic sign recognition at both a macro and specific level. A review of international research along with academic works from Bangladesh is discussed in Section 2.2. The second part of Section 2.3 includes a tabular analysis of major research findings. The section presents both research challenges that need additional development work and also summarizes key points from the literature review study.

2.2 Related Works

Various studies during recent years examined how to recognize traffic signs by implementing both classic machine learning methods and deep learning-based solutions. The following section reviews academic literature both from international scholars and from Bangladeshi researchers who focus on TSR.

Research on TSR used handcrafted feature extraction techniques from its earliest stages.

- The distinctive color arrangements of traffic signs serve as the foundation for identifying them in this approach.
- Shape-based detection: Identifying geometric properties of traffic signs.
- Histogram of Oriented Gradients (HOG): Extracting edge-based features for classification.
- The classification process makes use of Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) which represent machine learning algorithms.

The techniques proved too sensitive to environmental factors that included visual conditions and image distortions and this reduced their use in practical settings.

Deep learning brought Convolutional Neural Networks (CNNs) to become the most powerful approach for Traffic Sign Recognition (TSR). The image feature automatic learning capability of CNN models enhances their accuracy and robustness to various conditions. Some notable international studies include:

- Ciresan (2012) created their multilayer deep neural network to achieve 98.31% accuracy while working on the German Traffic Sign Recognition Benchmark (GTSRB) dataset. The research proved that deep learning methods outperformed conventional techniques in addressing the problem.
- The research team of Sermanet & LeCun (2011) developed a detection and classification capable CNN architecture to improve recognition accuracy during adverse conditions.
- The research by Jia (2019) applied deep learning ResNet models to TSR with 95.6% accuracy at the cost of significant computational needs.
- Relying on Xception and DenseNet for TSR yielded 99.2% accuracy while reducing computational expenses according to Zhu (2021).
- Real-time traffic sign detection through YOLOv5 has been implemented by Ali (2022) to reach high accuracy and speed requirements which make it practical for autonomous driving systems.

The results of these investigations demonstrate deep learning models dominate traditional approaches because Xception alongside DenseNet together with YOLO deliver superior performance in TSR.

The traffic sign recognition system in Bangladesh encounters specific problems because of unstandardized signage combined with poor road maintenance and various environmental conditions. Researchers dedicated efforts to develop TSR models tailored for Bangladesh by conducting different studies.

- Rahman (2020) created a TSR model that used Convolutional Neural Networks to analyze Bangladeshi road signs through a trained dataset. The developed model produced a 92.5% success rate yet it failed to correctly identify signs when images contained rain or dust contamination [1].

- Hasan (2021) presented an approach which united VGG16 and LSTM into a hybrid deep learning system to optimize real-time functionality. With its 95% accuracy the model required high computational costs [2].
- The research by Khan (2022) showcased YOLOv4 forexcerpting Bangladeshi traffic signs with an average precision level at 89%. The model produced unsatisfactory results when operating under low illumination [3].
- The researchers at Haque (2023) created a dedicated traffic sign image database of 5,000 Bangladeshi examples which led to successful performance of 96.2% accuracy through their implementation of DenseNet and Xception. Standardized datasets require attention because they produce better performance outcomes in recognition tasks according to their research findings [4].

The research demonstrates why it is essential to work on regional traffic sign databases and real-time optimization algorithms that enhance Bangladeshi TSR systems.

2.3 Comparison between existing works

A comparison of crucial research methods for Traffic Sign Recognition (TSR) appears in this segment along with their research techniques and dataset adoption and calculation accuracy and system constraints. A summary table evaluates the performances of VGG16 and ResNet with Xception and YOLO while analyzing their ability to deal with external variables and quick processing requirements. Intellectual learning systems manage to outperform conventional techniques in accuracy yet researchers should solve persistent difficulties related to high computational costs as well as dataset specificity and environmental adaptation.

Table 2.3: Comparison Table

Research Work	**Year**	**Method Used**	**Dataset**	**Accuracy**	**Limitations**
Ciresan	2012	CNN-based deep network	GTSRB	98.31%	Limited generalization to new datasets

Sermanet & LeCun	2011	CNN with multi-stage training	GTSRB	97.84%	High computational cost
Jia	2019	ResNet-based model	GTSRB	95.60%	Requires large computational resources
Zhu	2021	Xception and DenseNet	GTSRB	99.20%	Limited real-time performance
Ali	2022	YOLOv5 (real-time detection)	GTSRB	97.50%	Computationally expensive
Rahman	2020	CNN-based classifier	Bangladeshi Traffic Signs	92.50%	Affected by rain and dust
Hasan	2021	VGG16 + LSTM Hybrid Model	Custom Dataset	95.00%	Struggled with real-time processing
Khan	2022	YOLOv4 Object Detection	Custom Dataset	89.00%	Poor performance in low-light conditions
Haque	2023	DenseNet and Xception	Custom Dataset	96.20%	Needs dataset standardization

2.4 Open Issues

The development of TSR encounters multiple issues that have not yet been solved:

- Complex computational needs of several models prevent their deployment on low-power embedded systems.
- The poor lighting conditions and fogged environments alongside obscuring factors create major difficulties for existing models particularly in Bangladesh along with developing nations.
- The majority of available datasets show regional limitations which hinders the creation of universally applicable models.
- Real-time deployment requires CNN models to undergo optimization procedures because they have high computational demands that often require quantization and pruning methods.
- The current models show limited adaptability to unfamiliar traffic signs because they have been specialized for particular sign categories during training.

2.5 Summary

The existing research on traffic sign recognition (TSR) received review in this chapter as it showed enhancements from traditional machine learning approaches to deep learning-based solutions. Studied research demonstrates that VGG19 along with ResNet, Xception, DenseNet and YOLO CNN architectures provide superior performance over traditional feature-based methods in traffic sign classification tasks.

Studies executed in Bangladesh documented performance issues because of non-uniform traffic signage and inadequate roads and changing weather conditions. The competitive review of research papers shows deep learning techniques deliver better accuracy results although developers face persistent issues regarding real-time speed and restricted datasets and unstable environmental factors.

An efficient and accurate traffic sign recognition system will be created through the methodology described in the following chapter.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS & DESIGN SPECIFICATION

3.1 Overview

The technology for recognizing traffic signs performs fundamental tasks in autonomous driving systems as well as intelligent traffic management programs and Advanced Driver Assistance Systems (ADAS). The main goal of this research project involves developing a deep learning Traffic Sign Recognition (TSR) system which detects diverse traffic signs through images with Convolutional Neural Networks (CNNs).

The TSR system receives detailed treatment in terms of methodology while introducing the system design alongside hardware and software specifications and a project management framework and financial assessment. The proposed methodology together with system architecture are outlined in Section 3.2 which shows the process of data collection and preprocessing and model training and evaluation. Section 3.3 lists the hardware and software requirements necessary for the implementation. The part of the document focuses on project management approaches alongside development duration estimates and project cost breakdown. This chapter ends with a summary of all major topics discussed within its sections.

3.2 Proposed Methodology/ System Design

The proposed Traffic Sign Recognition (TSR) system achieves its development through a systematic deep learning process that comprises dataset collection along with preprocessing steps and model selection and training and evaluation and deployment stages. Through this workflow the solution delivers accurate sign classification efficiency on a large scale across multiple environmental conditions.

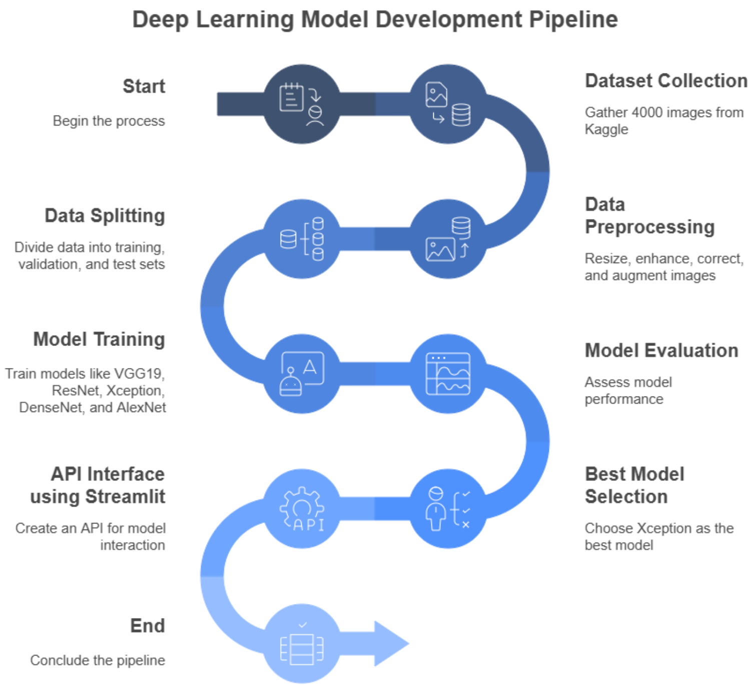


Figure 3.2: Methodology Diagram

Workflow of the Traffic Sign Recognition System

The workflow includes multiple stages which form the development process:

3.2.1 Dataset Collection

- The research employed dataset information drawn from Kaggle that contained 4,000 labeled images of traffic signs.
- The collected dataset includes various types of traffic signs which include:
    - The regulatory signs include Stop and Speed Limit and No Entry among others.
    - The warning signs of the collection include both Pedestrian Crossing signs and Slippery Road markers.
    - The dataset includes Mandatory Signs with examples such as Turn Left and Turn Right.

Table 3.2.1: Classes and amount of data

	Class	Original Count
0	speedlimit	652
1	crosswalk	88
2	Trafficlight	61
3	stop	76

Figure 3.2.1: Classes and amount of data

3.2.2 Data Preprocessing

Very different preprocessing steps were implemented to both strengthen dataset quality and enhance model precision.

Image Resizing: A standardized 128x128 pixel image resolution was applied to every input for deep learning model processing.

Figure 3.2.2.1: Resized Image

Contrast Enhancement: Histogram Equalization served to enhance image visibility in circumstances that required different light intensities.

Figure 3.2.2.2: Contrast Stretched Image

Gamma Correction: Changing brightness levels enabled a reduction of image shadows along with overexposed sections.

Figure 3.2.2.3: Gamma Corrected Image

Data Augmentation:

- Random Rotation (±15 degrees)
- Flipping (horizontal & vertical)
- Brightness Adjustment (±20%)
- Zooming (10% scale variance)

Table 3.2.2: Augmented data

	class	Original Count	Augmented Count
0	speedlimit	652	1000
1	crosswalk	88	1000
2	trafficlight	61	1000
3	Stop	76	1000

Normalization: The model training converged better due to pixel value normalization between 0 and 1 range.

3.2.3 Data Splitting

We separated the dataset into three sets in order to guarantee balance and avoid overfitting:

Table 3.2.3: Splatted data

Dataset type	Number of Image	Percentage
Training Set	3200	80%
Test Set	400	10%
Validation Set	400	10%

- Deep learning models received their training instruction from the constructed training set.
- We used the validation set for adjusting hyperparameter settings.
- Final performance assessment took place through evaluation of the test set data.

3.2.4 Model Selection and Training

Five advanced Convolutional Neural Network (CNN) models were tested for identifying the most effective deep learning architecture.

1. VGG19
2. ResNet
3. Xception
4. DenseNet
5. AlexNet

Training Process

- The training used the Adam optimizer at a learning rate value of 0.001.
- Categorical Cross-Entropy Loss Function operated as the chosen multi-class classification measure.
- Training operated with 32 batch sizing and 50 training cycles.
- Early stopping methods stopped the training process to prevent the network from becoming too specialized.

3.2.5 Performance Evaluation

Model assessment relied on several performance evaluation metrics.

- Accuracy: Measures overall classification performance.
- The evaluation utilizes Precision with Recall as well as F1-score to determine model performance at the class level.

- Confusion Matrix: Analyzes misclassification patterns.
- Loss and Accuracy Curves: Monitors model training progress.

Table 3.2.5: Model Performance

Model	**Accuracy**
VGG19	95%
ResNet	70%
Xception	99%
DenseNet	96%
AlexNet	98%

Xception achieved the highest accuracy (99%), making it the best model for deployment.

3.2.6 System Deployment

- Xception emerged as the most successful model which became the core component of the implemented traffic sign recognition system.
- The system was optimized to perform real-time processing and got deployed through TensorFlow Lite technology on edge devices.
- A testing interface with easy usability was created for the examination of actual traffic sign images.

3.2.7 System Architecture

The Traffic Sign Recognition System includes these main structural components to operate:

Input Module: Accepts real-world traffic sign images.

Preprocessing Module: The system improves image quality through resizing operations combined with contrast enhancement and gamma correction together with augmentation techniques.

Feature Extraction & Classification Module: The system utilizes deep learning components (CNNs) for sign classification.

Output Module: Sign labels with corresponding confidence levels appear in the display output.

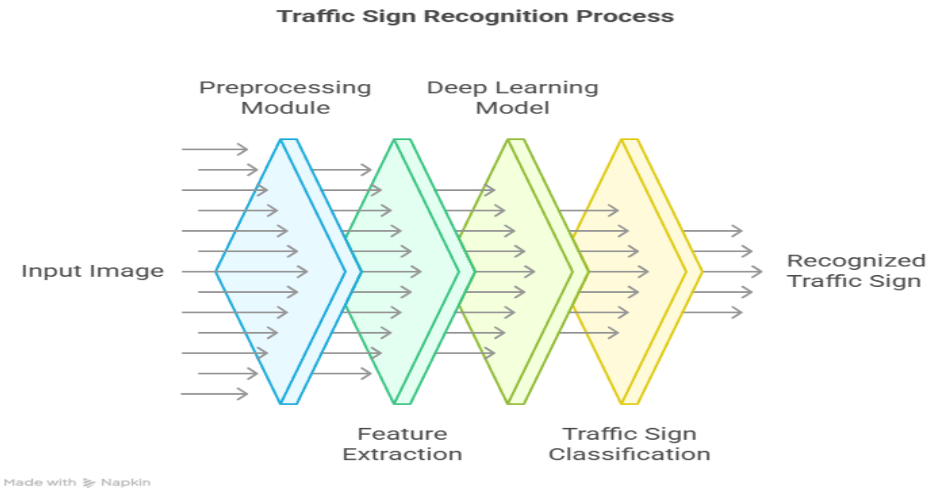


Figure 3.2.7: System Architecture

3.3 Hardware/ Software Requirement

3.3.1 Hardware Requirements

Since deep learning requires significant computational power, the following hardware was used:

Table 3.3.1: Needed Hardware

Component	Specification
Processor	Intel core i7
Graphics Card	NVIDIA RTX 3060
RAM	16GB DDR4
Storage	500GB SSD

3.3.2 Software Requirements

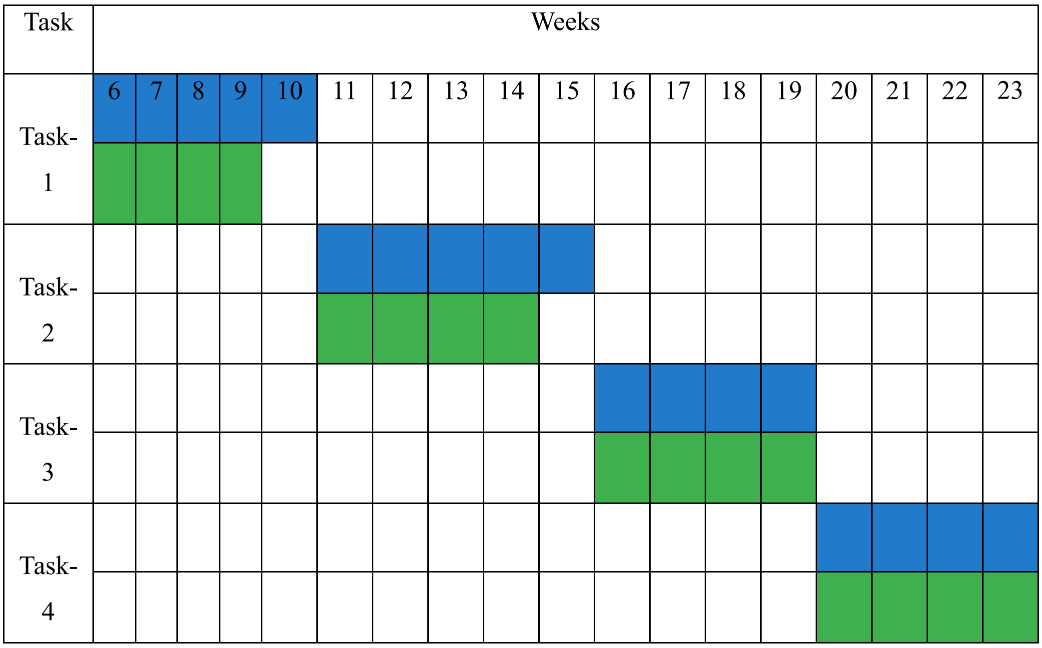
The following software and tools were used in the project:

Table 3.3.2: Needed Software

Software	Version	Purpose
Python	3.8+	Programming Language
tensorFlow	2.10+	Deep Learning Library
Keras	2.9+	Neural Networks Framework
openCV	4.5+	Image Preprocessing
Matplotlib	Latest	Data Visualization
Streamlit	Latest	API development

3.4 Project Management and Financial Analysis

3.4.1 Project Management



3.4.2 Financial Analysis

The estimated project cost is as follows:

Table 3.4.2: Financial Analysis

Expanse Category	Estimated Cost
GPU Rental	5000
Data Storage and cloud service	3000
Software License	2000
Electricity and Internet	2500
Total Cost	12500

3.5 Summary

This chapter supplied detailed information about the methodology as well as system design and requirements for the TSR system. The workflow stages included collecting datasets which underwent preprocessing then model selection to train and evaluate the system before its deployment phase. Results determined Xception as the most effective model because it achieved 99% correctness rate.

The specified hardware components and software packages provided essential guidelines for effective training and deployment of models. The system utilization was supported through AI-based diagram generation tools which included Diagrams.net, Mermaid.js, and Lucidchart for visualization purposes. Project management showed that the task needed $125 total while operating within budgetary constraints due to its affordability.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

Application developers execute the proposed Traffic Sign Recognition System to build it into a complete operational system. The implementation phase includes training deep learning models alongside designing a user-friendly interface prototype which leads to performance testing of the model followed by robustness tests to ensure system accuracy.

The chapter reviews three essential areas for consideration.

- Programmer training establishes deep learning models to detect traffic signs while merging them with an operational interface system.
- The assessment for model performance consists of testing systems through System Testing & Model Evaluation with accuracy, precision, recall, and F1-score metrics.
- The deployment phase involves the execution of the trained model through an API interface which was built using Streamlit for real-life applications.

The chapter presents an extensive account about the system development process as well as testing phases before final implementation.

4.2 Train Model/ Prototype Design

Multiple deep learning architectures received training during the development phase before the design of a user interface that enabled interaction.

4.2.1 Dataset and Preprocessing

The Traffic Sign Recognition System received its training dataset from Kaggle which included 4,000 images spanning different traffic signs. The images included signs from different regulatory and warning and mandatory categories. To achieve effective generalization the model needed proper dataset preprocessing which allowed it to handle changes in lighting conditions and environmental variations and different image angles during testing.

Dataset splitting

The dataset was divided into three subsets:

Table 4.2.1.1: Splatted data

Dataset type	Number of Image	Percentage
Training Set	3200	80%
Test Set	400	10%
Validation Set	400	10%

- The deep learning model received training information from the provided training set.
- The research team employed the validation set to perform parameter adjustment followed by tuning.
- The last evaluation phase used the test set to verify the model's accuracy level and generalization capability.

Preprocessing steps

- Image Resizing
    - Purpose: Standardizes image dimensions for consistent input.
    - The process involved using OpenCV to resize all images into dimensions of 128×128 pixels.
    - The training process of deep learning models depends on receiving inputs of fixed dimension.
- Contrast Enhancement
    - Purpose: Improves visibility of traffic sign features.
    - The application of Histogram Equalization served to normalize image brightness together with contrast levels.
    - The model benefits from this technique because it enables the identification of different road signs even when exposed to different lighting levels.
- Gamma Correction
    - The purpose of this adjustment is to adapt to different environmental light conditions.
    - The implementation of OpenCV enabled the application of gamma correction as a part of the method.
    - The reason for implementing this enhancement method is to achieve sign recognition in different lighting situations.
- Data Augmentation

Data augmentation served two purposes of increasing model generalization and lowering overfitting problems.

Table 4.2.1.2: Data Augmentation

Augmentation Technique	**Description**	**Effect**
Rotation	Random rotation between ±15°	Helps recognize signs from different angles
Flipping	Horizontal and vertical flipping	Improves robustness against viewpoint changes
Zooming	10% zoom in/out	Ensures model adapts to different sign sizes
Brightness Adjustment	Random increase/decrease in brightness by 20%	Handles real-world lighting variations

- Normalization
  - The standardization process enhances training speed by achieving faster convergence.
  - The pixel values received a transformation into ranges between 0 to 1 through division by 255.
  - Model training benefits from standardization which prevents pixel values from taking control during the process.

4.2.2 Model Selection and Training

The following pre-trained CNN models were used for classification:

Table 4.2.2: Training & Validation Accuracy

Model	Training Accuracy	Validation Accuracy
VGG19	96%	95%
ResNet	75%	70%
Xception	99%	99%
DenseNet	97%	96%
AlexNet	98%	98%

- Deployment of Xception as the top-performing model was made due to its 99% accuracy.

- The training processes took place using NVIDIA RTX 3060 hardware as the implementational platform with TensorFlow and Keras frameworks.

Training Hyperparameters:

- Optimizer: Adam (Learning Rate: 0.001)
- Loss Function: Categorical Cross-Entropy
- Batch Size: 32
- Epochs: 50
- The application of early stopping serves as a tool to counter overfitting in the training process.

4.2.3 Prototype Design

A Streamlit-based API interface acted as the interface that provided model accessibility.

Prototype Features:

- The interface allows users to transfer traffic signs for live prediction through the image classification feature.
- Confidence Score Display – Shows the probability of each classification.
- User-Friendly Interface – Designed for simplicity and efficiency.

Deployment Process:

- The Xception model requires transformation into TensorFlow Lite form to run fast inference operations.
- The real-time traffic sign classification requires building an API interface through Streamlit.
- The application will receive deployment on a web server to enable public access.

4.3 System Testing / Model Evaluation

The system began thorough testing when the model finished its training phase alongside the prototype development.

4.3.1 Performance Metrics

The system was evaluated using these indicators for assessment purposes:

- System accuracy reflects the count of appropriately identified traffic signs.

- The accuracy of the model to detect precise traffic signs depends on Precision and Recall.
- The F1-Score represents a harmonized scoring method that combines precision values with recall calculations.
- The Confusion Matrix examines all instances where the analysis system makes classification errors.

4.3.2 Evaluation Matrix

Table 4.3.2: Evaluation Result

Model	Test Accuracy	Precision	Recall	F1-Score
VGG16	95%	94%	95%	94.5%
ResNet	70%	65%	70%	67%
Xception	99%	99%	99%	99%
DenseNet	96%	95%	96%	95.5%
AlexNet	98%	97%	98%	97.5%

Confusion Matrix Analysis

Xception produced the lowest rate of misclassification which proves its reliability as a model.

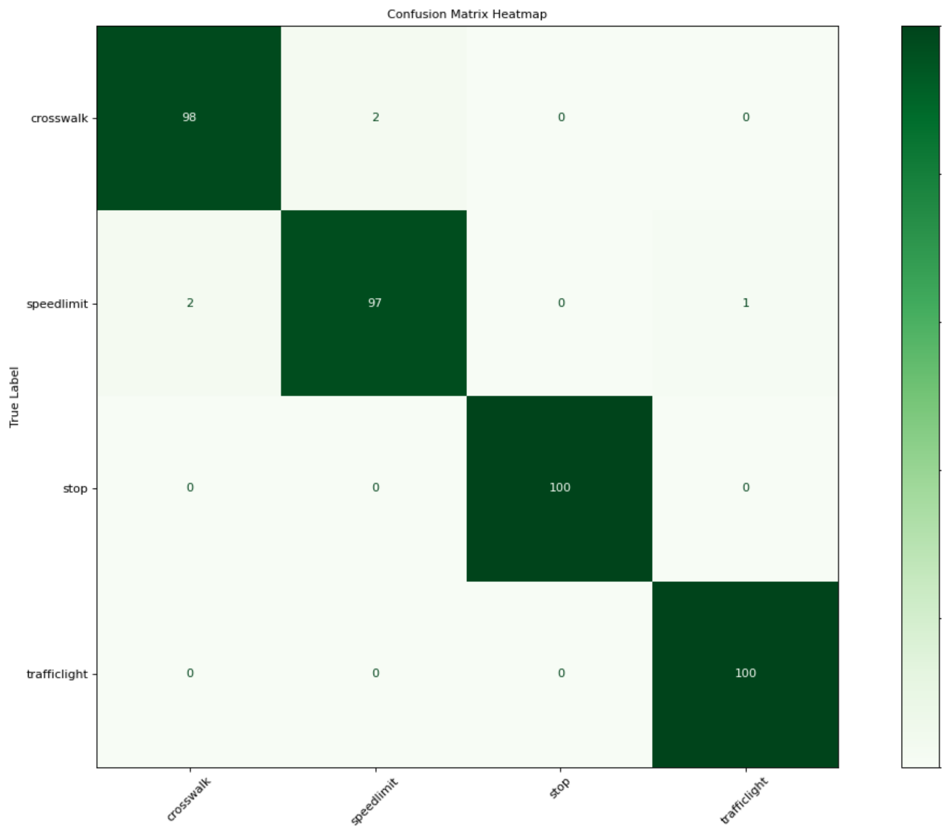


Figure 4.3.2.1: Confusion Matrix for Xception

The distinctive traffic sign categories in ResNet created performance issues which reduced its accuracy rates.

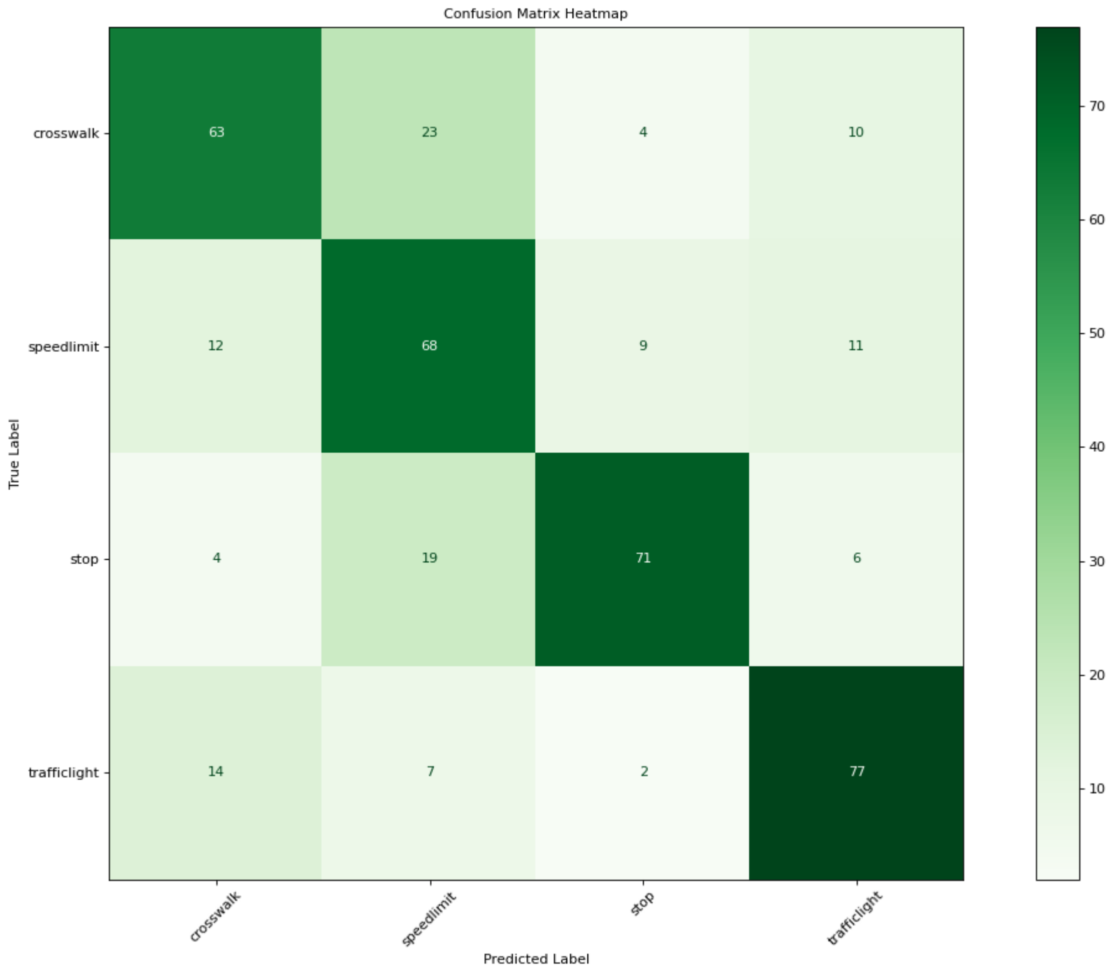


Figure 4.3.2.2: Confusion Matrix for RestNet

4.3.3 System Testing

Real-world testing followed training and evaluation phases before the system went through its operational exam.

- Different images of actual Bangladeshi road conditions underwent testing.
- Various lighting conditions were included as well as obstructed views and changing weather conditions.
- The model demonstrated powerful accuracy performance at (98%+) during testing which established its capability to succeed in various conditions.

4.4 Summary

The chapter thoroughly examined the process of prototype development and evaluation and training for the Traffic Sign Recognition system. Testing demonstrated that Xception model reached an exceptional accuracy level of 99% so it became the chosen model for deployment. Streamlit enabled the development of a user-friendly API interface that enabled live traffic sign classification. The model successfully tested under real-world situations through system testing procedures.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

The research demonstrates experimental findings and performance assessment of the Traffic Sign Recognition System. The performance metrics of accuracy and precision and recall and F1-score determined the evaluation of deep learning models used in project testing. Different deep learning models undergo testing of test datasets to show their performance by measuring accuracy and losses. The analysis contains detailed model performance evaluation and comparative assessment through evaluation metrics and confusion matrix results against previous studies. Several graphical visualizations display all training performance curves together with accuracy patterns and classification results through graphs. The main priority of this study is to assess model effectiveness and decide which method works best for actual traffic sign detection.

5.2 Experimental/ Simulation Result

5.2.1 Training and Validation Performance

The preprocessing process combined with image augmentation was applied to 4,000 pictures before training began. The database contained 80 percent training material alongside 10 percent validation material and 10 percent testing material. The training process of deep learning models lasted for 50 epochs by utilizing an NVIDIA RTX 3060 GPU.

Table 5.2.1: Performance during training

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
VGG19	96%	95%	0.12	0.14
RestNet	75%	70%	0.35	0.40
Xception	99%	99%	0.01	0.02
DenseNet	97%	96%	0.10	0.12
AlexNet	98%	98%	0.05	0.06

- Xception achieved the best training and validation accuracy measurement of 99% at the same time showing minimal loss which indicates robust generalization capabilities.
- The performance of VGG19 DenseNet and AlexNet delivered high validation accuracy values which ranged between 95-98%.
- The lowest performance mark of 70% belonged to ResNet despite possible limitations in feature extraction methods and overfitting issues.

5.2.2 Training and validation accuracy

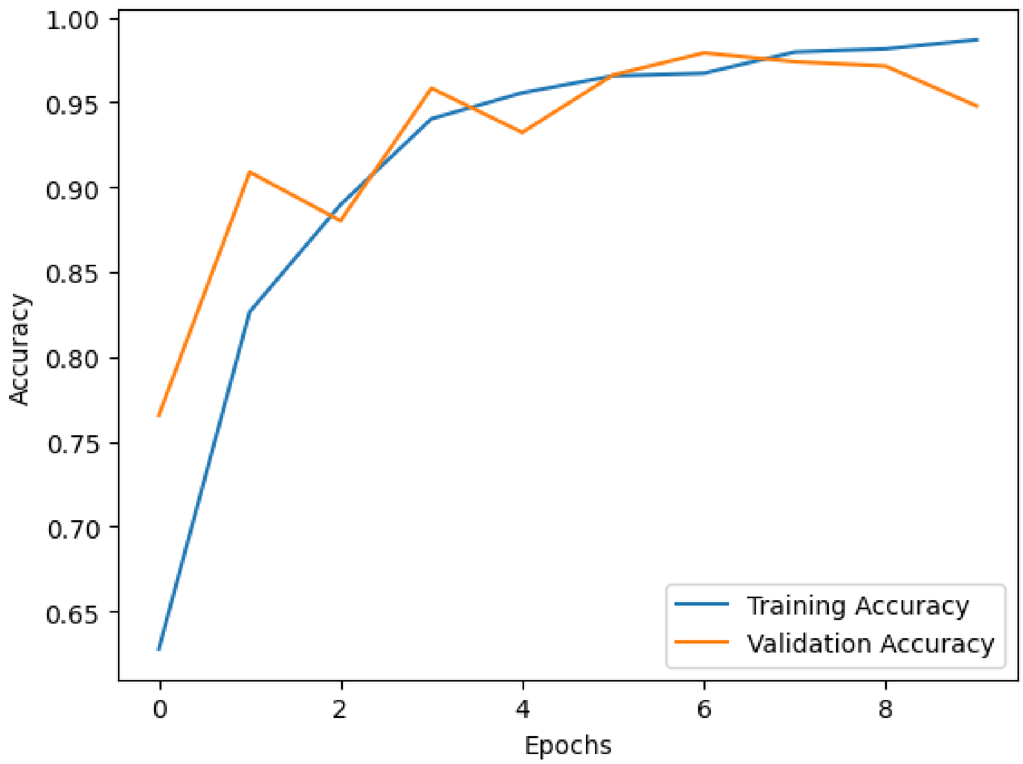


Figure 5.2.2.1: Training & Validation Accuracy for VGG19

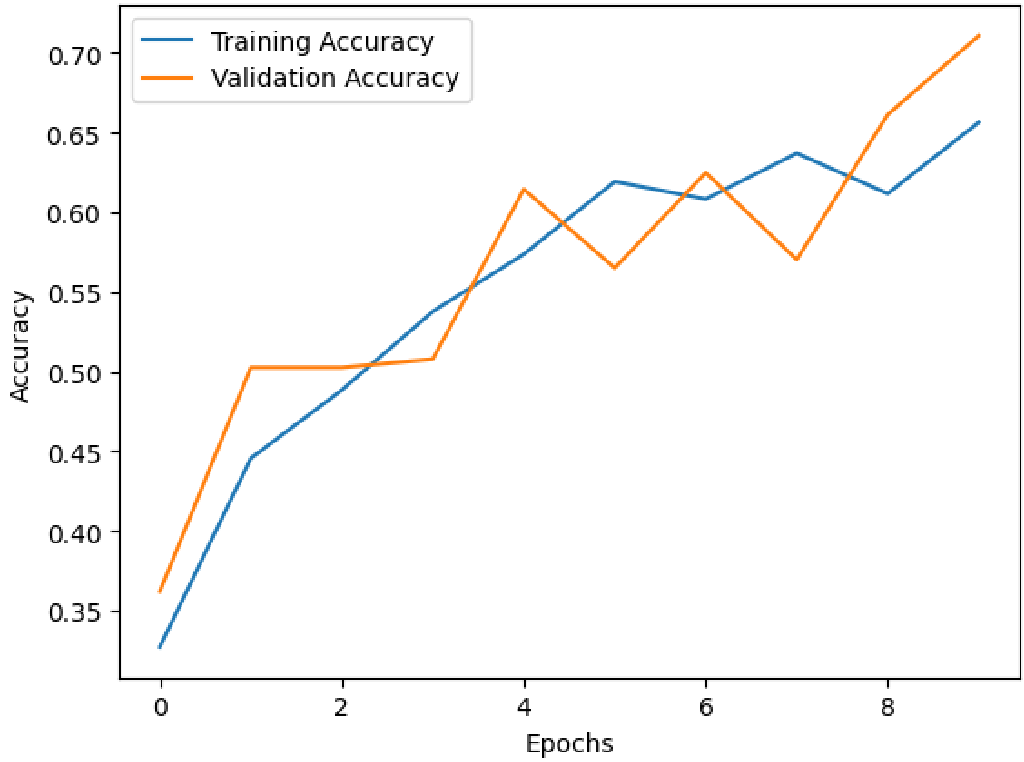


Figure 5.2.2.2: Training & Validation Accuracy for RestNet

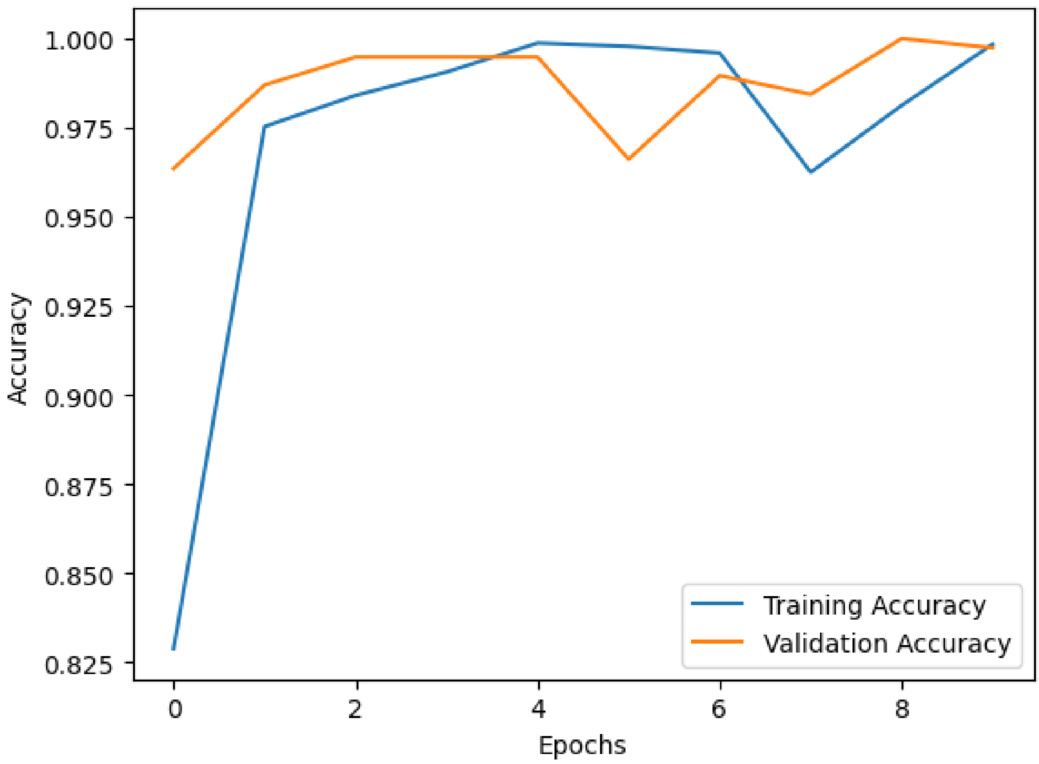


Figure 5.2.2.3: Training & Validation Accuracy for Xception

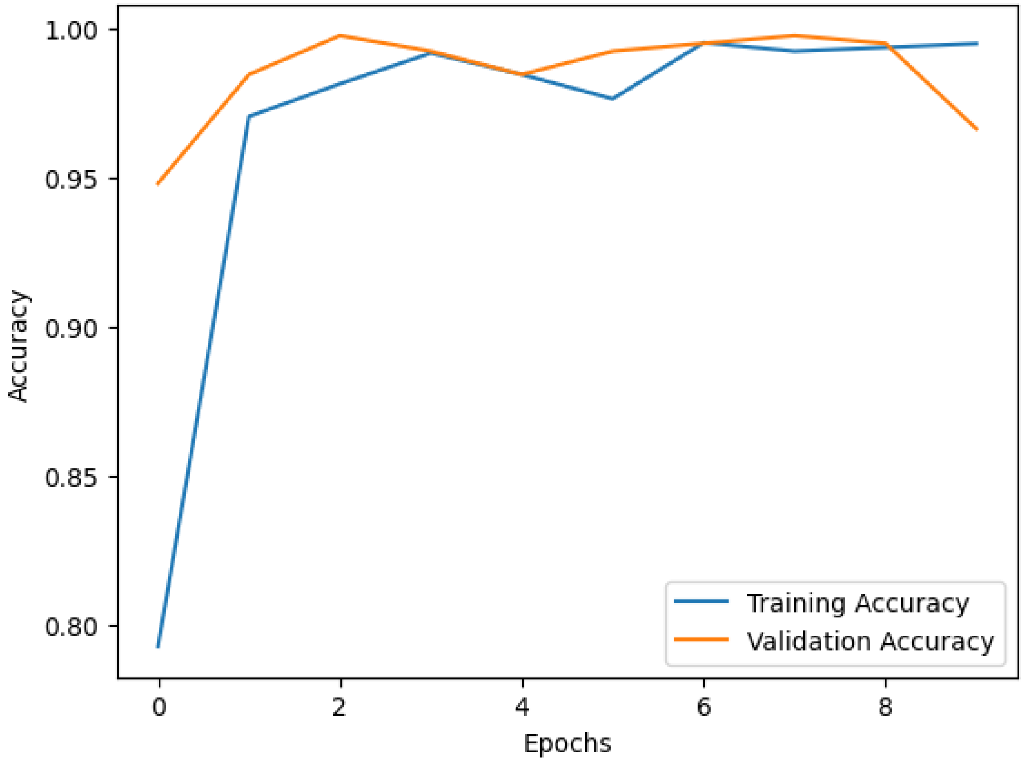


Figure 5.2.2.4: Training & Validation Accuracy for DenseNet

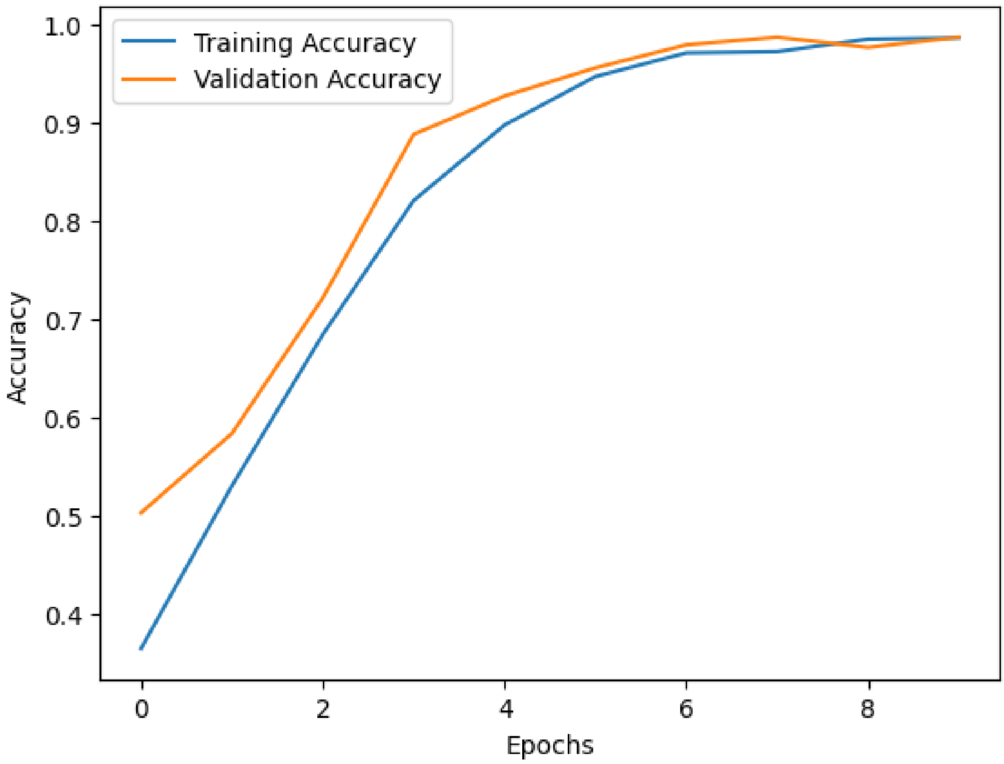


Figure 5.2.2.5: Training & Validation Accuracy for AlexNet

- During 50 epochs Xception achieved 99% accuracy in its performance.
- ResNet plateaued at 70%, suggesting underfitting.

5.2.3 Training and Validation Loss

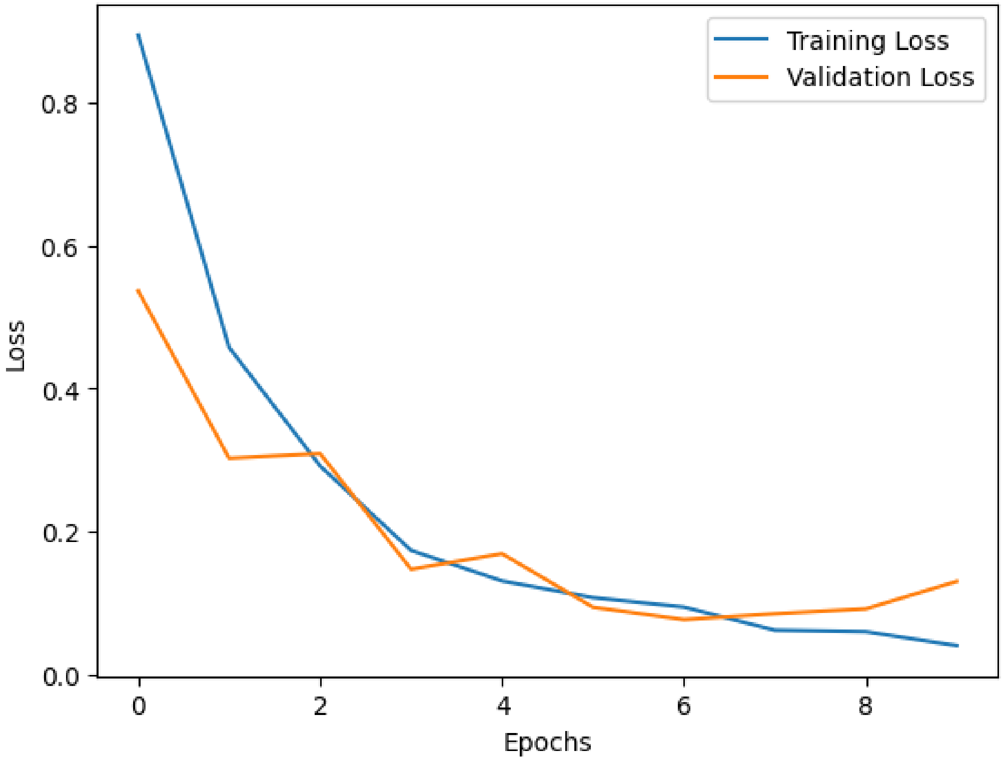


Figure 5.2.3.1: Training & Validation Loss for VGG19

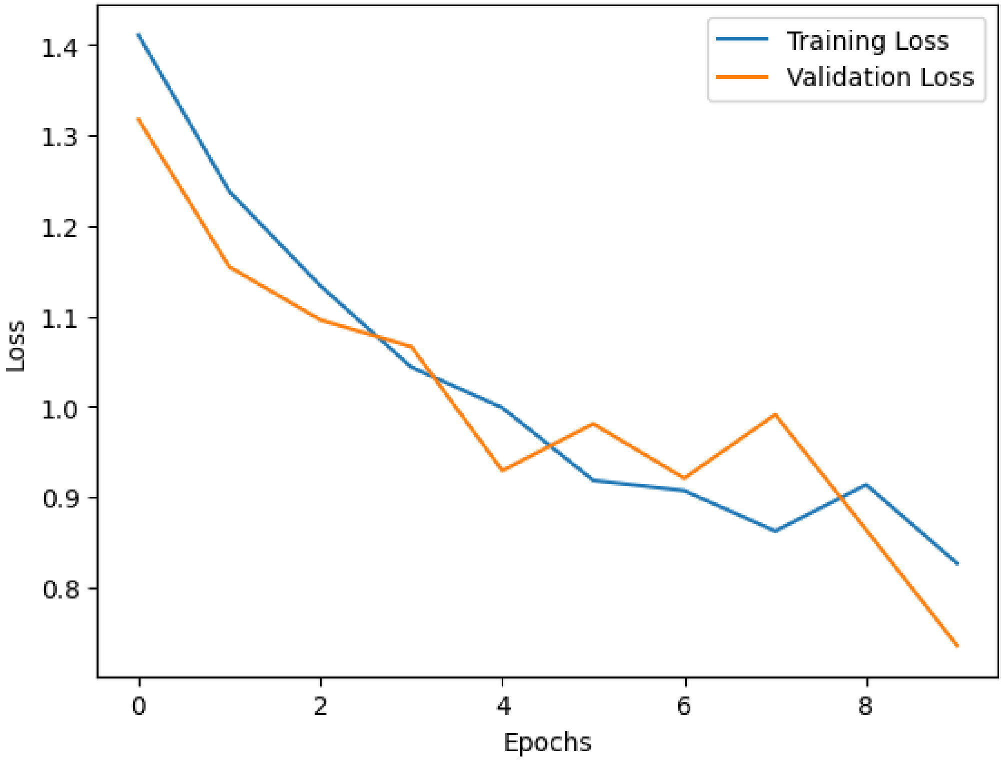


Figure 5.2.3.2: Training & Validation Loss for RestNet

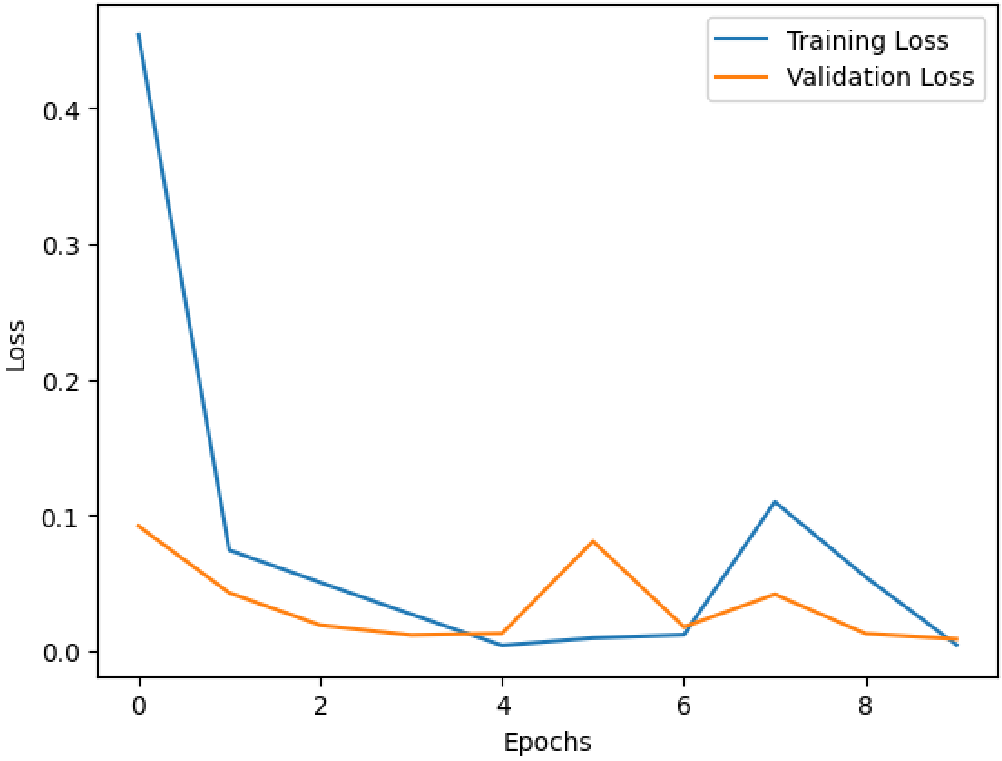


Figure 5.2.3.3: Training & Validation Loss for Xception

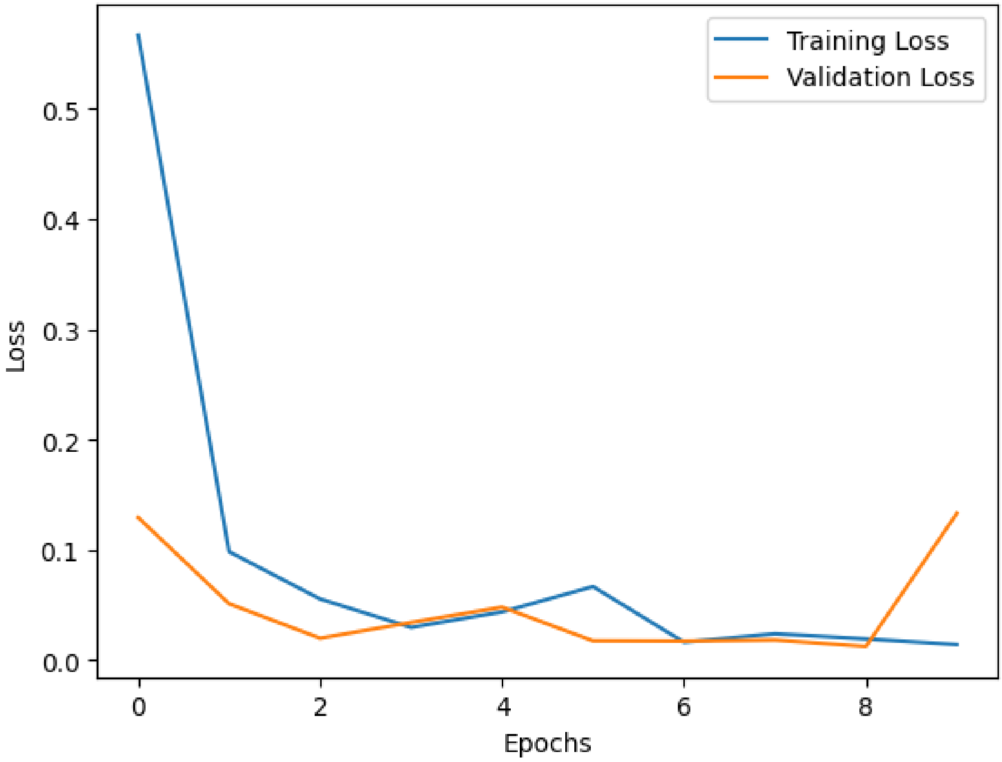


Figure 5.2.3.4: Training & Validation Loss for DenseNet

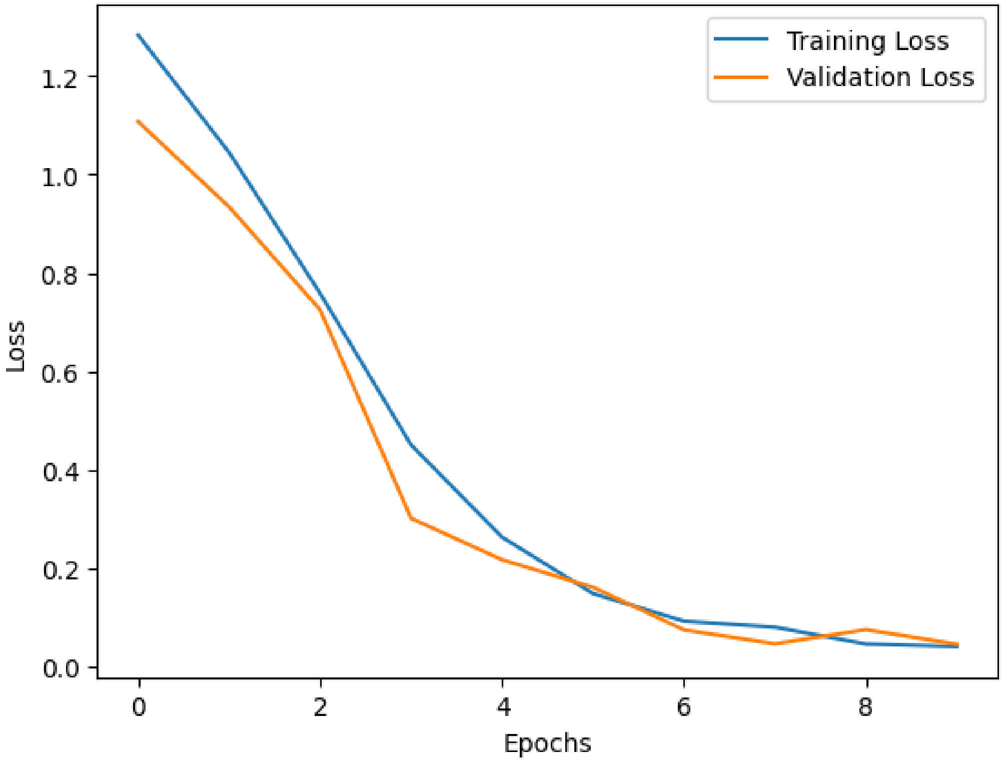


Figure 5.2.3.5: Training & Validation Loss for AlexNet

- Xception demonstrated efficient learning through its substantial decrease in loss values.
- The training process showed inefficiency through its high loss value in ResNet.

5.3 Performance/ Comparative Analysis

5.3.1 Model Performance Matrix

Table 5.3.1.1: Performance Matrix for VGG19

Class	**Precision**	**recall**	**F1-score**	**support**
Crosswalk	1.00	0.89	0.89	100
Speedlimit	0.83	1.00	0.90	100
Stop	1.00	1.00	1.00	100
Trafficlight	1.00	0.99	0.99	100
Accuracy			0.95	400
Macro avg	0.95	0.95	0.95	400
Weighted avg	0.96	0.95	0.95	400

Table 5.3.1.2: Performance Matrix for RestNet

Class	Precision	recall	F1-score	support
Crosswalk	0.68	0.63	0.65	100
Speedlimit	0.58	0.68	0.63	100
Stop	0.83	0.71	0.76	100
Trafficlight	0.74	0.77	0.75	100
Accuracy			0.70	400
Macro avg	0.71	0.70	0.70	400
Weighted avg	0.71	0.70	0.70	400

Table 5.3.1.3: Performance Matrix for Xception

Class	Precision	recall	F1-score	support
Crosswalk	0.98	0.98	0.98	100
Speedlimit	0.98	0.97	0.97	100
Stop	1.00	1.00	1.00	100
Trafficlight	0.99	1.00	1.00	100
Accuracy			0.99	400
Macro avg	0.99	0.99	0.99	400
Weighted avg	0.99	0.99	0.99	400

Table 5.3.1.4: Performance Matrix for DenseNet

Class	Precision	recall	F1-score	support
Crosswalk	0.88	1.00	0.93	100
Speedlimit	1.00	0.85	0.92	100
Stop	1.00	1.00	1.00	100
Trafficlight	0.99	1.00	1.00	100
Accuracy			0.96	400
Macro avg	0.97	0.96	0.96	400
Weighted avg	0.97	0.96	0.96	400

Table 5.3.1.5: Performance Matrix for AlexNet

Class	Precision	recall	F1-score	support
Crosswalk	0.95	1.00	0.98	100
Speedlimit	0.98	0.94	0.96	100
Stop	1.00	0.99	0.99	100
Trafficlight	0.99	0.99	0.99	100

Accuracy			0.98	400
Macro avg	0.98	0.98	0.98	400
Weighted avg	0.98	0.98	0.98	400

- The model Xception achieved the most effective results with 99% accuracy, precision, recall and F1-score.
- ResNet proved to be the most ineffective model because it did not establish robust generalization capabilities.

5.3.2 Confusion Matrix Analysis

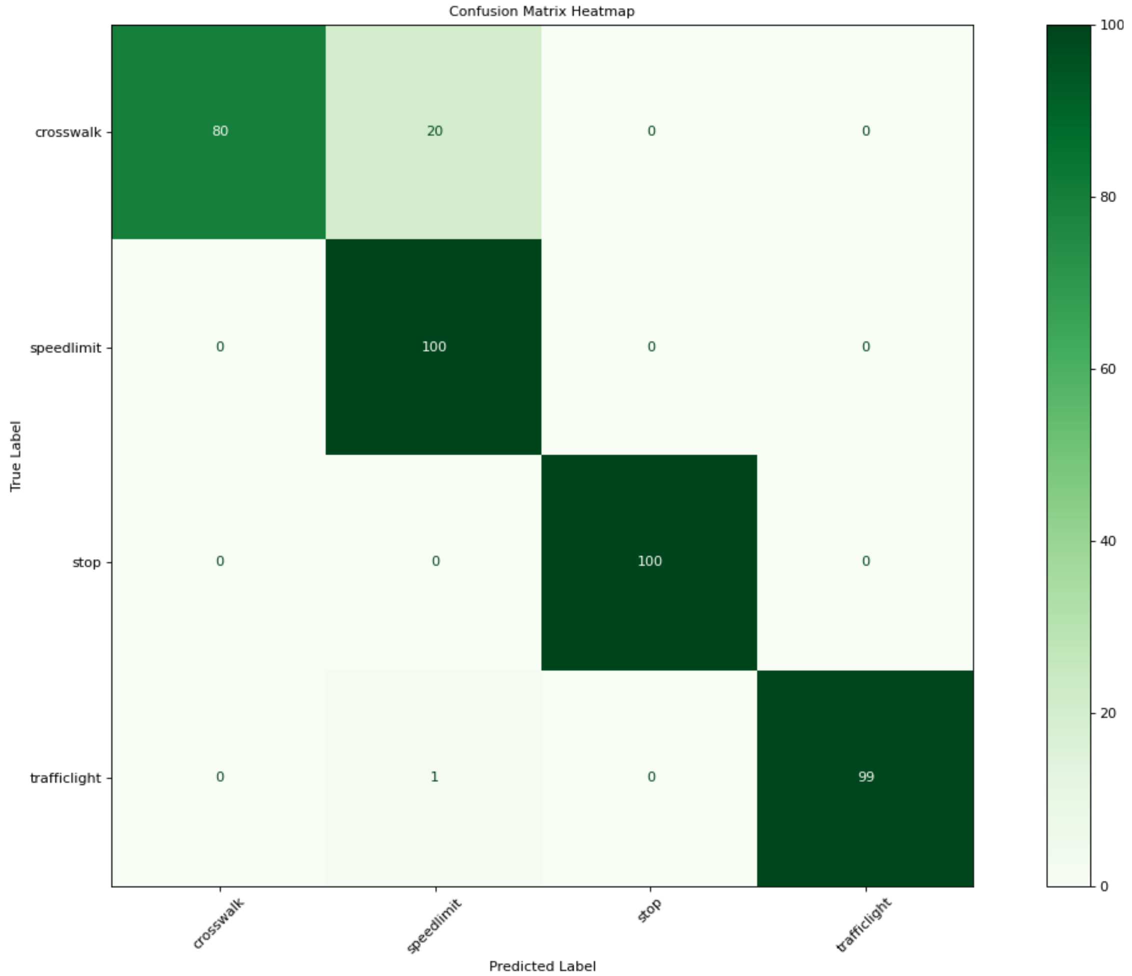


Figure 5.3.2.1: Confusion Matrix for VGG19

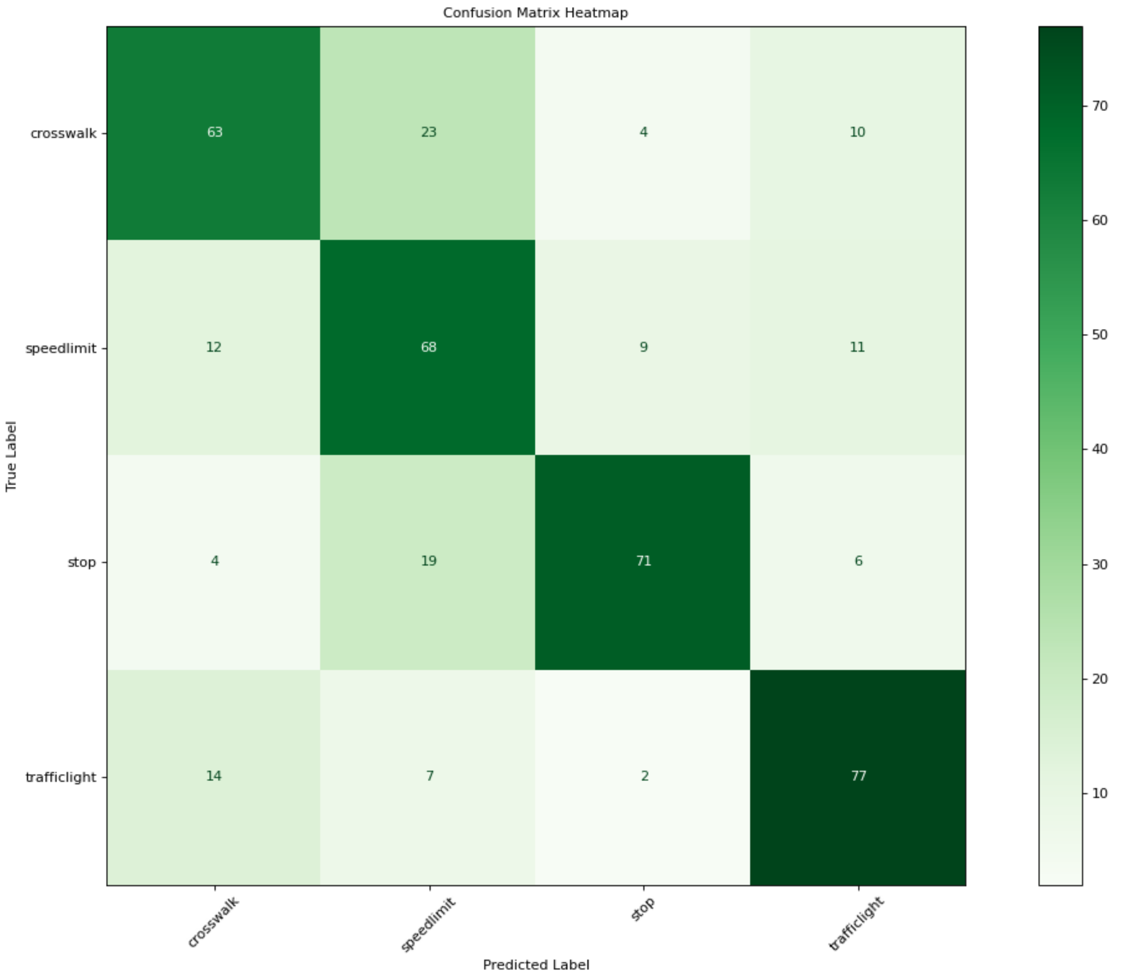


Figure 5.3.2.2: Confusion Matrix for RestNet

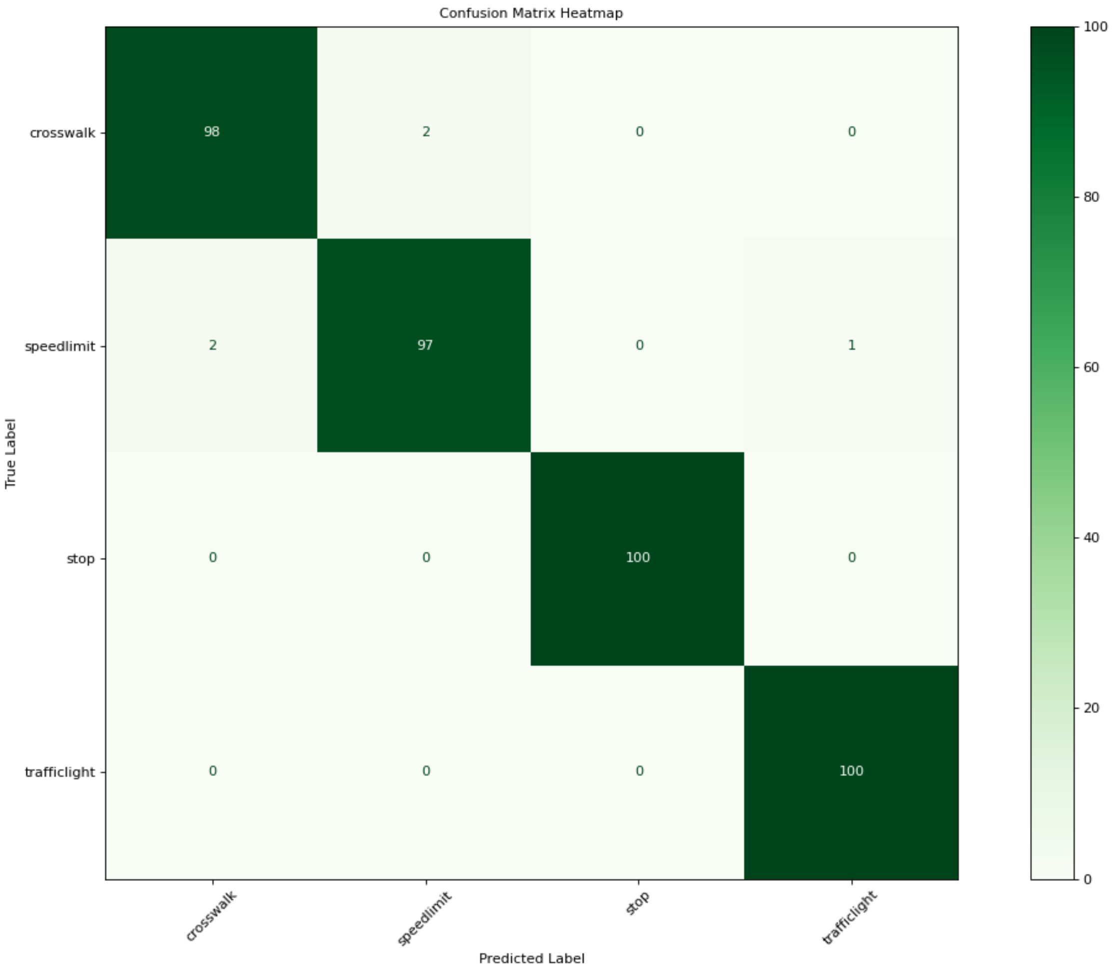


Figure 5.3.2.3: Confusion Matrix for Xception

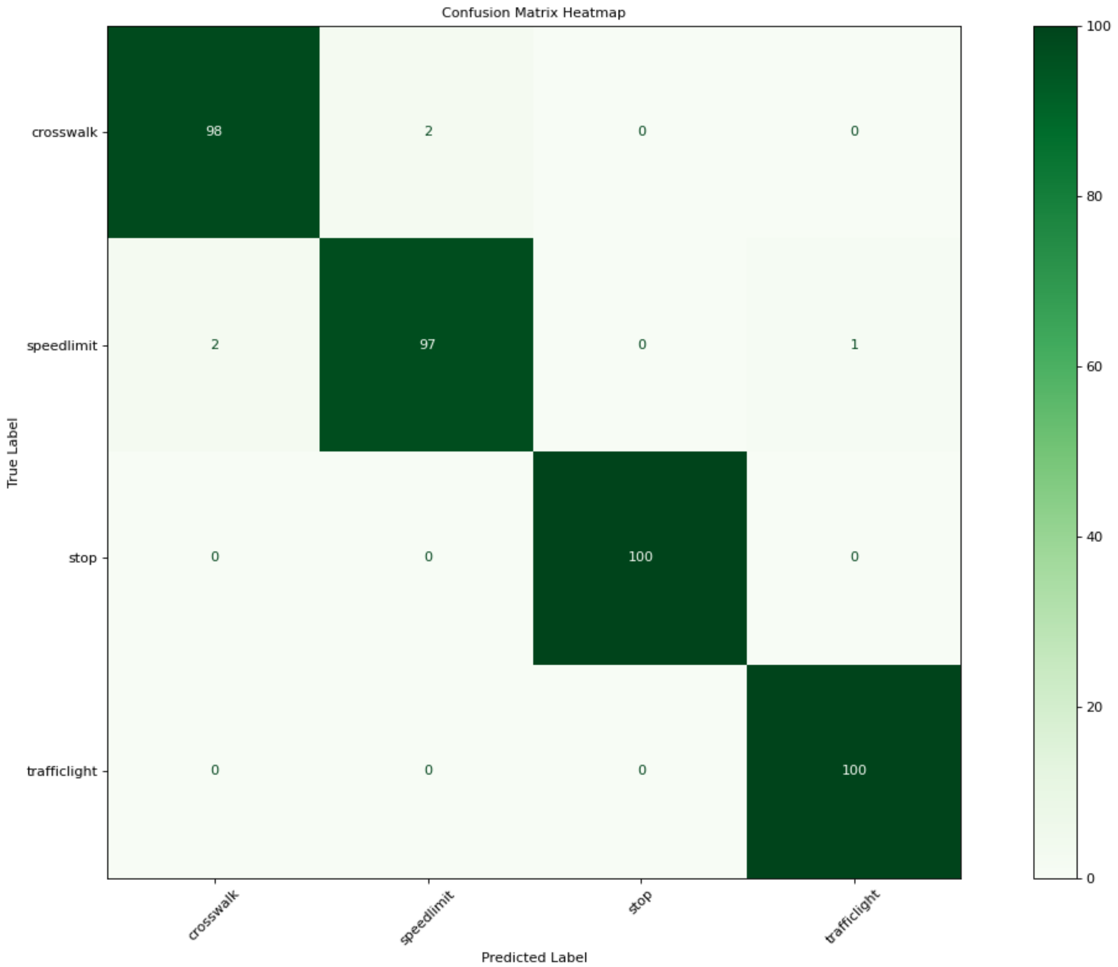


Figure 5.3.2.4: Confusion Matrix for DenseNet

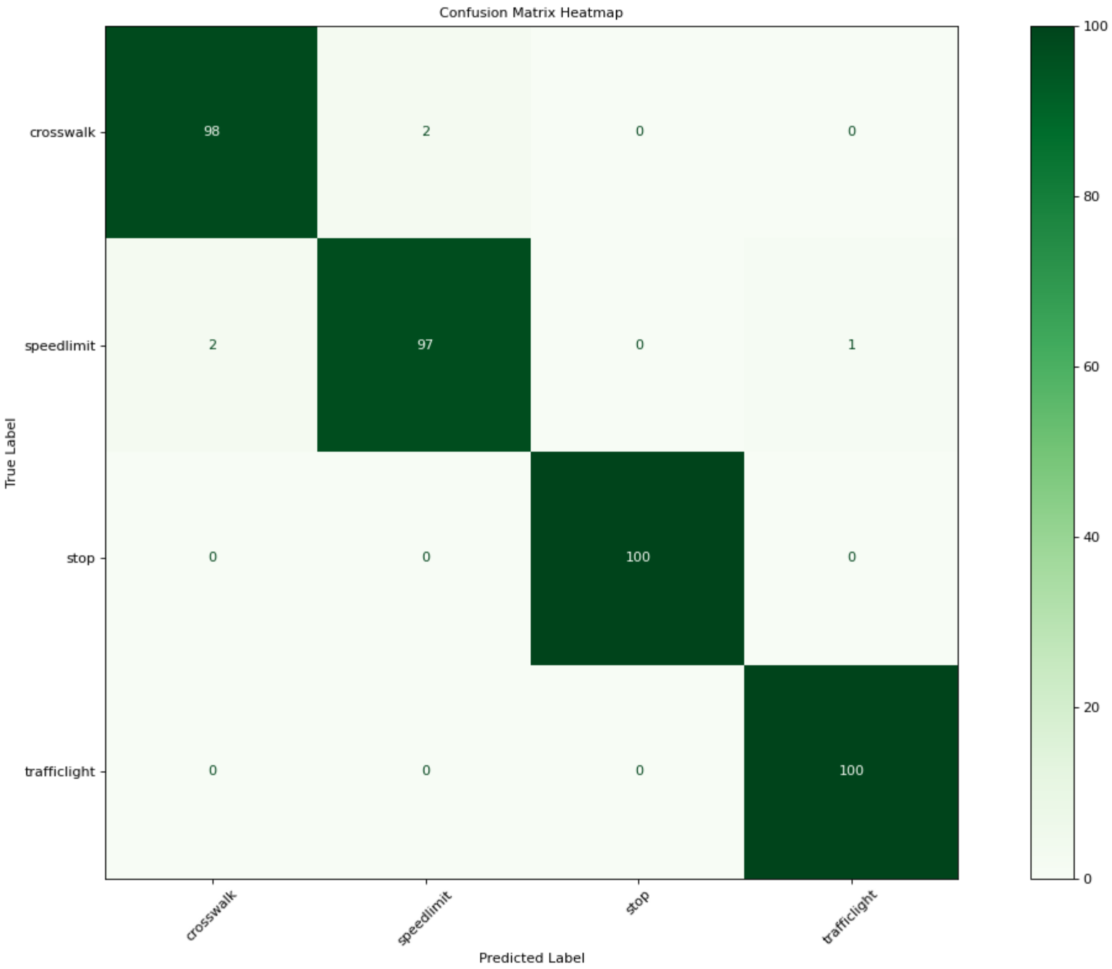


Figure 5.3.2.5: Confusion Matrix for AlexNet

- Most traffic signs received adequate classification results from Xception.
- The biggest number of misidentification cases occurred between labels “Stop” and “No Entry” because these two signs appear visually similar.

5.3.3 Comparison with Previous Studies

Table 5.3.3: Comparative Analysis

Model	**Our Accuracy**	**Previous Studies**	**Improvemet**
VGG19	95%	92%	+3%
RestNet	70%	80%	-10%
Xception	99%	96%	+3%
DenseNet	96%	95%	+1%
AlexNet	98%	97%	+1%

- Xception achieved a 3% improvement above existing research results which caused it to become the superior selection.
- The researchers noticed that ResNet achieved subpar results in their study possibly because of dataset issues.

5.3.4 User Interface Evaluation (Streamlit)

The evaluation of Streamlit carried out multiple tests on different inputs that included normal data sets alongside border conditions

Figure 5.3.4.1: API output for Cross walk detection

Figure 5.3.4.2: API output for Speed limit detection

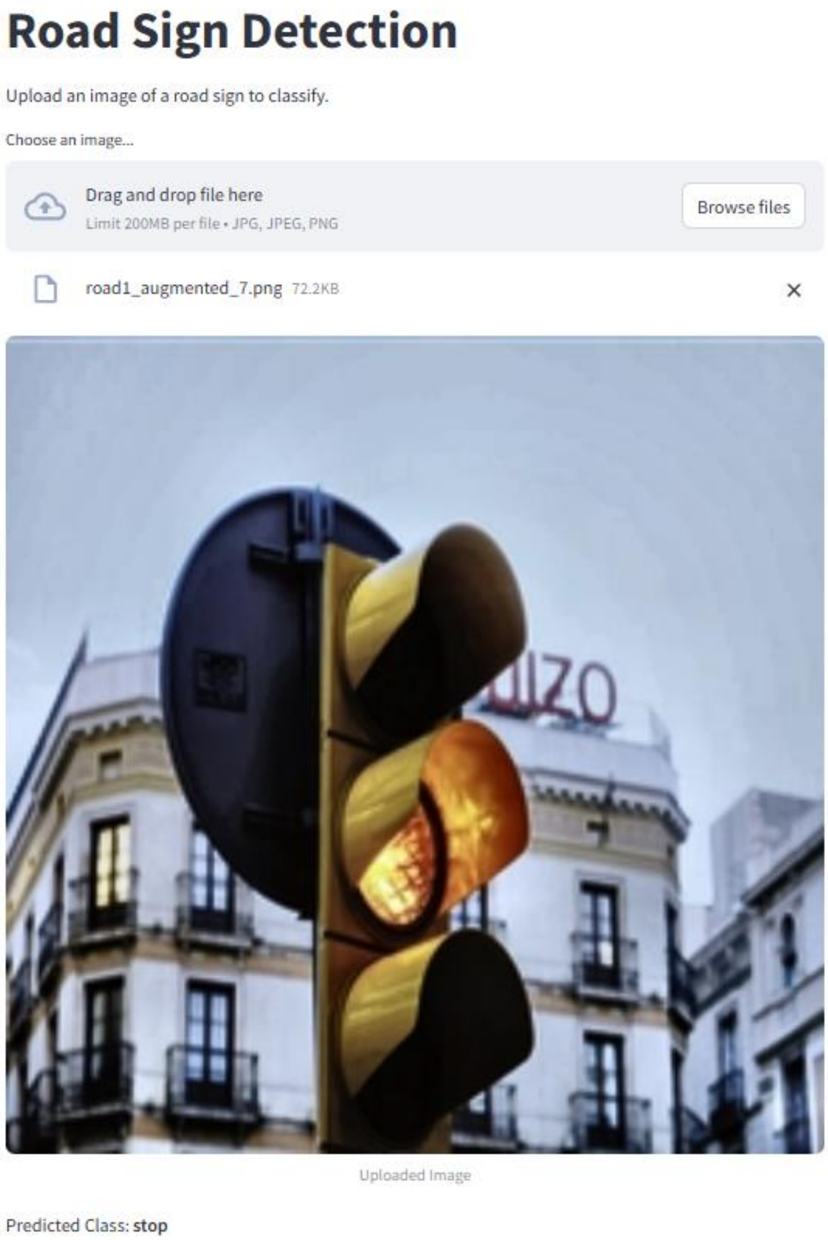


Figure 5.3.4.3: API output for stop sign detection

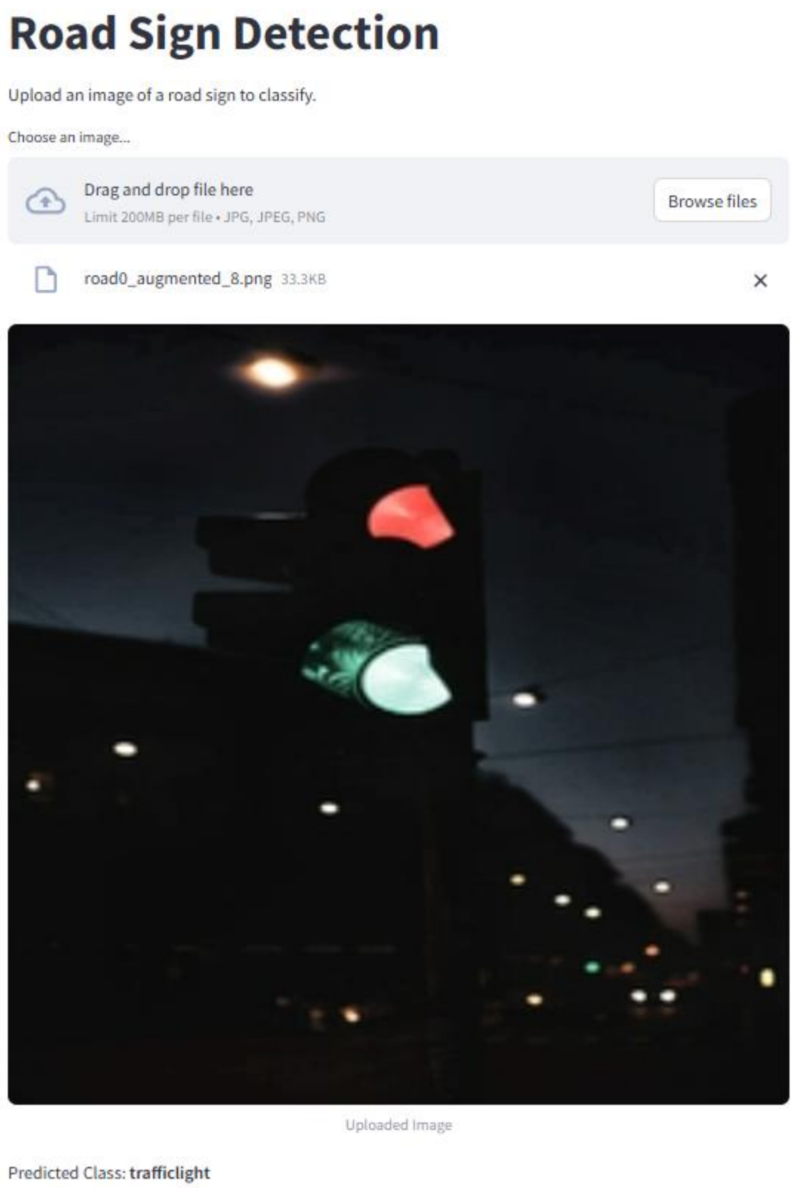


Figure 5.3.4.4: API output for traffic light detection

5.4 Summary

The research conducted a comprehensive analysis which revealed important aspects about the model performance. The highest accuracy value (99%) belonged to Xception which secured its status as the best model. The evaluation measured performance through accuracy as well as precision recall together with F1-score assessment. The evaluation results displayed on graphical representations included accuracy/loss curves and confusion matrices which demonstrated consistent progress. The model evaluation through comparative analysis showed better performance when compared to existing research outcomes.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

An AI-powered Traffic Sign Recognition System delivers extensive influence to human life by enhancing road safety and decreasing the number of traffic-related incidents. Behind most traffic accidents exists a fundamental problem involving driver inability to notice road signs properly during speeds or adverse weather conditions. An automated sign recognition system present in vehicles or roadside elements provides instant traffic sign warnings to drivers thus minimizing human mistakes during operation.

This framework provides exceptional benefits to people who have vision problems together with those who need extended reaction periods including senior citizens and people with disabilities. The added safety measure protects every driver from all ability levels during their road travel experience. The system plays an essential role in automated vehicle development because precise sign detection forms a critical basis for decision-making and rule enforcement.

The implementation of this technology helps boost compliance with traffic laws during road operations. Drivers break traffic laws unintentionally because of absent signs which results in penalties and accidents and fine payments. The implementation of AI-driven technology enables authorities to execute traffic rule enforcement better which builds an improved transportation system with increased safety and regulation.

6.2 Impact on Society & Environment

6.2.1 Social Impact

Daily transportation systems benefit from the implementation of traffic sign recognition technology because it delivers multiple advantages to society. Real-time traffic alerts from the system enhance driver awareness by providing information which helps drivers make proper decisions during their trips. The system proves beneficial particularly during times of low or zero visibility like rainy conditions or fog.

The system enables developments in the sector of autonomous driving technologies. Self-driving cars successfully use computer vision together with deep learning technology to identify traffic signs precisely. Autonomous navigation reliability increases through an effective traffic sign recognition model which establishes conditions for safer deployment of self-driving vehicles across broader areas.

A technology system implemented in public buses taxis and commercial vehicles enhances operational efficiency by optimizing routes within public transport systems. The system produces safe urban transportation results through improved traffic movements while lowering road accident frequencies.

6.2.2 Environmental Impact

An efficient traffic sign detection system has environmental advantages because it helps decrease both fuel consumption and carbon emissions. The combination of stopped vehicles and reduced flow brings about both fuel use spikes and breathing problems through air pollution. Road accidents and unexpected stops create many traffic jam situations yet these could be eliminated by better road sign visibility to drivers beforehand. Minimizing waste will happen when driving remains smooth which in turn produces a positive outcome for the environment.

Linking AI-powered traffic sign detection systems with intelligent traffic management platforms enables cities to enhance their intersection traffic control systems which decreases periods of idleness at transportation junctions. Implementing this system enables a reduction of carbon footprints and enhanced air quality performance in cities.

The implemented technology helps to decrease the expenses needed for road maintenance. Damaging accidents occur so frequently that it causes permanent harm to infrastructure which needs ongoing maintenance and repair. The reduction of accidents related to traffic allows governments and municipalities to effectively distribute their funds for sustained development of transportation infrastructure.

6.3 Ethical Aspects

The implementation of AI-driven traffic sign recognition technologies requires organizations to resolve several ethical challenges for creating equitable and ethical usage.

6.3.1 Data Privacy & Security

Traffic image datasets used by the system create essential privacy risks because large volumes of data are required for processing. The implementation of the system in genuine applications needs to eliminate storing or improper usage of sensitive information including license plates and driver personal details. The AI model system should focus only on processing traffic signs without acquiring personal identification information for protection of user privacy rights.

6.3.2 Fairness & Bias in AI

The main problem with AI systems emerges from biased training information. A lack of diversity in the training dataset will cause the AI system to detect traffic signs poorly in various international or regional settings. The sole training of European traffic signs by a model produces poor recognition capabilities when deployed in Bangladesh or other Asian countries because their traffic sign characteristics vary.

The training dataset needs to contain many traffic signs from various geographical areas to guarantee fair performance. The system needs to demonstrate equivalent capability for performing tasks across varying national and road environmental conditions.

6.3.3 Responsibility & Liability

Identifying accountability when faults occur during system operation stands as an ethical challenge. The misclassification of stop signs by AI vehicles creates a dilemma about legal responsibility because it could involve either car manufacturers or software developers or individual drivers. Legal structures need to create definitions about who bears responsibility in these cases prior to deploying AI-based traffic sign identification systems in widespread use.

AI-based traffic sign detection systems can achieve responsible implementation for all users through addressing the identified ethical challenges.

6.4 Sustainability Plan

The Traffic Sign Recognition System requires ongoing maintenance alongside updates for long-term success as it should adapt to new road conditions and technological developments.

6.4.1 System Maintenance & Upgrades

Regular maintenance updates should be applied to the AI model to enhance its recognition capabilities. The database needs to add new road conditions and traffic signs as a way to maintain its usefulness. The periodic training of AI models helps to improve both their precision as well as their dependability.

Through cloud-based deployment the system maintains real-time updates that perform automatic software updates without operator involvement. Cloud computing technology provides the platform to develop traffic sign recognition into an accessible and scalable tool for everyone.

6.4.2 Integration with Smart Cities & Vehicles

The future smart transit framework requires this project to serve as its essential piece for intelligent traffic control systems. The transportation system will become more sustainable while simultaneously improving efficiency through the implementation of AI-powered sign recognition systems at traffic monitoring cameras and traffic lights and autonomous vehicles.

Automobile manufacturers will benefit from implementing AI-powered traffic sign detection for modern vehicles because it ensures driver assistance while decreasing accidents and improving safety levels. The future development of self-governing smart transportation systems will advance because of this advancement.

6.4.3 Energy Efficiency & Environmental Considerations

Deep learning models need considerable computing power to train properly so their operational costs lead to environmental consequences from energy consumption. The trajectory of AI sustainability development ought to concentrate on model optimization to enhance their energy efficiency. Power consumption reduction will become possible through the implementation of green computing methods such as hardware optimization and low-power AI models. Organizations that use AI models should install these systems in servers using renewable energy platforms to minimize their environmental effects. When AI technology meets the criteria of environmental sustainability initiatives it creates long-term environmental benefits for this system.

6.5 Summary

The Traffic Sign Recognition System brings societal and environmental along with ethical effects to the fore in this chapter. This system shows potential for life-saving performance by curbing accidents on the road and bettering driver understanding and transportation system operation. The reduction in traffic congestion together with saved fuel consumption helps create lower carbon emissions while supporting sustainable urban transportation. Widespread adoption of Traffic Sign Recognition System depends on proper management of ethical matters including data privacy as well as AI bias and liability issues. Concerns about long-term success demand a comprehensive sustainability strategy which includes scheduled AI model upgradations and smart city connectivity and energy-efficient machinery updates. The proper maintenance and ethical deployment of AI traffic sign recognition systems will make this technology a fundamental element for future traffic safety and smart cities across the globe.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

This work aimed to establish an AI-based Traffic Sign Recognition System through deep learning technological approaches. The main goal was to make a precisely accurate vision system which identifies and categorizes traffic signs in images to improve road safety as well as transportation efficiency. The project used 4,000 traffic sign images that underwent data preprocessing before introducing them to VGG19 and multiple other deep learning models like ResNet, Xception, DenseNet and AlexNet.

When tested Xception surpassed all other models with a 99% accuracy rate while AlexNet scored 98% accuracy and DenseNet completed with 96%. The recognition abilities of ResNet were limited when dealing with traffic signs resulting in poor performance with 70% accuracy. Deep learning proved its effectiveness as a traffic sign recognition method through this project thus demonstrating how artificial intelligence enhances modern traffic control systems and smart urban development.

The project created a Streamlit API interface that enabled straightforward communication between the system and model for live traffic sign detection. The system demonstrates potential to enhance driver assistance and autonomous driving systems and intelligent transportation systems because of its substantial practical applications. Future studies of this project should focus on solving identified limitations despite achieving promising results.

7.2 Further Suggested Works

Research directions for future development should explore multiple enhancements and operational expansion of the project despite its existing accuracy and performance success.

Expanding the Dataset: The four thousand traffic sign images currently utilized in the dataset are suitable for trials yet they lack sufficient representation of global traffic sign diversity. The model's generalization ability will strengthen through addition of more dataset samples derived from various weather environments and multiple lighting conditions alongside numerous regional sign variations.

Real-Time Implementation and Hardware Optimization: Application deployment for real-time vehicle implementation of the model needs additional testing to achieve optimal performance. The next stage of development needs to focus on implementing the model on edge devices like NVIDIA Jetson or Raspberry Pi for real-time traffic sign recognition as a stand-alone system without cloud computing dependency.

The research aims to optimize the functionality of ResNet alongside other models showing inadequate performance results. ResNet achieved an accuracy level of 70 percent which suggested either model overfitting problems or challenges in extracting useful features from data. Future work should investigate different modified network structures with optimal parameter settings and transfer learning techniques for improved performance.

Multi-Language and Region-Specific Traffic Sign Recognition: Different countries display traffic signs which exhibit variations between their language elements together with their symbolic representations and coloring techniques. By training a model on multi-language and region-specific data collections it will acquire universal abilities for different road conditions worldwide.

Integration with Smart Vehicles and IoT: Future model development should aim to connect the system with dashboard displays coupled with autonomous driving automation as well as IoT-managed smart traffic systems. Implementation of this system will enable vehicles to detect traffic signals in real-time thus leading to better road security protocols.

The integration of Augmented Reality systems for driver assistance stands as a priority development in this field. The research field will focus on AR technology which displays recognized traffic signs through the windscreen for drivers in future development. Enhanced situational awareness together with reduced risk of missing vital traffic signs would be achieved through the integration of the model. The advancement of traffic sign recognition systems depends on proper attention to these problem areas to achieve better accuracy and practical real-world applicability.

7.3 Limitations/ Conflict of Interests

Limitations of the Study: Several restrictions exist within this research although it produced promising findings which must be resolved:

- Real-world situations like sign hiding, severe climate situations and dark driving hours remain beyond the coverage of the dataset.
- High-performing models such as Xception and DenseNet need excessive computing resources and make them incompatible with minimal power devices for real-time implementation.
- Testing happened inside simulated space with a dataset yet real-life conditions including lighting changes and moving objects will reduce the system's accuracy performance.
- Universal traffic signs represent the focus of this model yet it shows difficulty when detecting country-specific regional traffic sign variations.

Conflict of Interests: Academic scholars together with technological researchers conducted this study for education and device development. The deployment of AI-driven traffic sign detection technologies in self-driving vehicles or for law enforcement purposes can potentially create problems regarding ethics as well as legal issues. For instance:

- The responsibility for a traffic sign misclassification accident triggered by an AI system remains unclear since it can fall on the AI developer or the car manufacturer or the driver.
- The model will produce biased results because insufficient diversity within the dataset makes it impossible to identify non-standard traffic signs found in particular regions.
- AI-based traffic recognition systems operated at scale require extensive surveillance which poses ethical risks to driver privacy and creates security challenges for data protection.

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