TEXT BASED BANGLA ROAD SIGN DETECTION USING PROPOSED DEEP LEARNING APPROACH

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "Text Based Bangla Road Sign Detection Using Proposed Deep Learning Approach", submitted by **Md. Shakib Al Hasan & Munimul Hoque Sazid** 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 B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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DECLARATION

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

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ABSTRACT

Traffic monitoring, driver assistance, and autonomous driving systems all depend on the identification of road signs. Road sign detection is vital for safety and advanced systems for drivers. In this context, this study is aimed at establishing a development of a deep learning approach for Bangla Road sign recognition using CNN. The dataset includes images linked to the 11 categories of Bangla Road signs such as “Traffic Merges from Left,” “Speed Limit 40 km,” among others. In this study, we compare the performance of VGG16, Xception, DenseNet201, ResNet50 and a CNN model developed particularly for this purpose to accurately identify these signs. The potential CNN architecture that the we propose is tailored for the issues of Bangla script and the enhancement of text-based road sign recognition. Frameworks such as TensorFlow and Keras were employed and the training and testing were performed on GPUs for faster computation. Conclusively, the CNN sees an accuracy of 96.41% by subjecting it to a process of testing/evaluation that considers it comparable with the benchmark models including VGG16 (99. 51%), Xception (99. 51%), DenseNet201 (96. 97%), and ResNet50 (96. 083). This study is useful in real life such as affairs related to traffic control and Self-driving cars in terms of CNN in Bangla Language. It adds knowledge to techniques in model enhancement, dataset acquisition, and performance assessment methodologies, which will open the door for further research on intelligent transportation systems based on deep learning technology.

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CHAPTER 1
INTRODUCTION

1.1 Overview

The cultivation Traffic management and road safety require the development of accurate and trustworthy road sign detection systems. This project, which focuses on the busy streets and highways of Dhaka, Bangladesh, aims to create a text-based system for detecting Bangla Road signs. The primary goals are to improve traffic control, vehicle awareness, and overall traffic safety in the area where it occurs. The two main goals of the project are to collect datasets and develop models. Understanding the importance of a carefully selected dataset, the project aims to collect a diverse set of photos of Bangla Road signs from various parts of Dhaka. The dataset includes eight different types of traffic signs, each with 1,000 photos. To address the issue of incomplete data, image augmentation methods are used to improve the dataset, ensuring that the model can function in a variety of situations. During the model development stage, a customized CNN architecture is proposed according to the features of Bangla Road signs. This custom model aims to provide a solution that has been specific to the specific challenges presented by the Bangla script by using its deep knowledge of the dataset's details. To determine which approach is most effective, the project presents a comparative analysis with popular transfer learning models, such as ResNet50, ResNet101, DenseNet201, and MobileNetV2. The primary goal is to provide a road sign detection system that is accurate, smart, and responsive to social differences while also taking into account the subtle language characteristics of Bangla. This project aims to provide an accurate system for traffic management authority by addressing local specifics and utilizing modern deep learning techniques, resulting in safer and more efficient public transportation in Dhaka. In addition to improving local road safety, our program wants to make significant contributions to machine learning and intelligent transportation systems.

1.2 Background and Present State

The project makes a lot of background knowledge and lots of literature on computer vision, deep learning, and automated transportation. The current research on road sign detection points out the importance of robust algorithms in achieving precise identification, particularly when taking language variances into account. The literature also highlights the effectiveness of transfer learning and Convolutional Neural Networks (CNNs) in image recognition tasks, which serves as a foundation for model development. Additionally, research on the language and cultural aspects of road signs points out how important it is to modify systems for specific local contexts. Notably, the Dhaka traffic management project highlights how urgently an in language aware road sign detection system is needed. This body of knowledge serves as the foundation, directing the design decisions and methodology and introducing the project into line with accepted practices and developments in the fields of machine learning, deep learning and transportation research.

1.3 Problem Statement

The justification for this research can be found in raising concerns of the need for intelligent transportation systems and the paucity of regional solutions. Currently available methods in road sign detection are designed for the commonly used languages while there is a lack of concern for other regional languages such as Bangla. To rectify this, we propose a novel deep learning-based solution for Bangla Road sign detection that is far more accurate than previous work. This is important for increasing the rates of correct identification of these signs, to enhance the reliability of road transport safety for general public and self-driven cars in Bangladesh and including advanced methodologies of smart transportation systems. Meeting this need will benefit the future studies and improvements of traffic management and safety level in the local area.

1.4 Objective

The objective of this project develops from an urgent need to improve road safety in Dhaka by addressing weaknesses in current traffic management systems. The language complexities of the Bangla script require a specialized approach to accurate road sign detection, prompting the creation of a dedicated system. The overarching goal is to develop a smart system that not only accurately recognizes Bangla Road signs but also takes into account Dhaka's unique cultural and language context. In this phase, our specific goals are in two ways. First, we are going to carefully curate a comprehensive dataset containing various images of Bangla Road signs from Dhaka's streets and highways. Second, we aim to create and evaluate the effectiveness of a customized Convolutional Neural Network (CNN) architecture designed for Bangla Road sign detection. At the same time, we will compare this to developed transfer learning models ResNet50, ResNet101, DenseNet201, and MobileNetV2 to determine the best approach for achieving high accuracy in Dhaka's complex landscape of road signs. Through these goals, we hope to make significant progress toward a safer and more culturally sensitive traffic management infrastructure.

1.5 Scope and Limitations

The justification for this research can be found in raising concerns of the need for intelligent transportation systems and the paucity of regional solutions. Currently available methods in road sign detection are designed for the commonly used languages while there is a lack of concern for other regional languages such as Bangla. To rectify this, we propose a novel deep learning-based solution for Bangla Road sign detection that is far more accurate than previous work. This is important for increasing the rates of correct identification of these signs, to enhance the reliability of road transport safety for general public and self-driven cars in Bangladesh and including advanced methodologies of smart transportation systems. Meeting this need will benefit the future studies and improvements of traffic management and safety level in the local area.

1.6 Report Organization

The organization of the report is intended in such a manner that it offers a broad understanding of the study conducted on Bangla Road sign recognition employing the deep learning algorithm. This segment defines the objectives of the research and its relevance in the field. The discussion of the literature focuses on the previous research on road sign recognition and the absence of previous work on Bangla Road signs. The chapter on the methodology explains the data acquisition, selection of CNN model and the training phases. In the last section of the paper as the system design and model evaluation, the authors briefly describe the structure and the results of the experiments for the models. The chapter on implementation outlines procedure in model development and use on an everyday basis. The chapter on a discussion of the experimental results describes the efficiency of various CNN configurations. Last of everything, the conclusion gives an overview of the works done in the project, including the achievements, challenges faced, and areas of improvement in case of future endeavors.

1.7 Summary

The expected outcome of this study is to develop a mechanism which can successfully identify Bangla Road signs with an acceptable degree of classification accuracy using deep learning techniques. We expect our proposed model to attain the state-of-art performance equivalent or even better, to models that have already been developed and currently in use such as VGG16, Xception, DenseNet201, ResNet50 among others. In particular, the custom CNN envisaged in this work should be capable of presenting competitive accuracy and time optimization that is apt for Bangla Road signs in view of their peculiar features. The current research also seeks to offer insights on practical approaches to avoid or minimize issues with datasets and their diversity, environment, and emerging techniques to improve model optimization, and make tangible improvements to intelligent transportation systems in the context of Bangladesh.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Most of the works in road sign recognition are based on deep learning approaches, more specifically CNN predominantly because of their effectiveness in image classification. Several works have utilized the architectures like VGG16, ResNet50, Xception, DenseNet201 for recognizing road signs in different languages and under different conditions. Many of these models have been proven to have quite high levels of accuracy in the recognition of road signs and therefore have been used to spur traffic monitoring, driver assist systems, auto mobile industry inclusive of the self-driving cars. An observation which needs mention in this regard is that there is a dearth of research work carried out in the realm of Bangla Road sign recognition. This study will try to meet this gap by assessing and comparing several CNN architectures on a newly created dataset of Bangla Road signs and thereby presenting important findings and a base for the future studies.

2.2 Related Works

Many facets of Bangla language processing and recognition experienced a dramatic revolution thanks to the development of deep learning techniques. This review summarizes current research on the use of machine learning algorithms and deep neural networks (DNNs) in various domains related to the Bangla language environment:

Banik, Bithi, et al. [1] proposed an algorithm made to recognize Bangla Road signs more accurately. The process used by the algorithm begins with the capture of images from real video scenes and then moves on to text detection, character segmentation, and character recognition using shape matrices. Each unique Bangla Road sign is given its own set of feature vectors, which are then used to train a neural network. The classification of new Bangla Road signs is then done with the help of this neural network. The system has the capacity to recognize road signs accurately, according to first trial data. Alom, Md Zahangir, et al. [2] utilized deep neural networks to improve the capabilities of handwritten Bangla digit recognition (HBDR). We introduce a number of methods, such as Deep Belief Network (DBN), Convolutional Neural Networks (CNN), CNN with dropout, CNN with dropout and Gaussian filters, and CNN with dropout and Gabor filters. These networks can extract and use feature information to enhance two-dimensional shape identification while being invariant to translation, scaling, and other pattern distortions. The CMATERdb 3.1.1 Bangla numeral image database was used to systematically analyze the suggested technique, which had a recognition rate of 98.78%. Current cutting-edge algorithms for HBDR are outperformed by this strategy, CNN with Gabor features and dropout. Roy, Saikat, et al. [3] proposed a novel deep learning approach for recognizing isolated compound characters in handwritten Bangla, setting a new standard for recognition accuracy on the CMATERdb 3.1.3.3 dataset. The method entails greedy layer-wise training of Deep Convolutional Neural Networks (DCNN) in a supervised setting, with the speed of convergence accelerated using the RMSProp algorithm. Comparisons with ordinary DCNNs and conventional shallow learning techniques utilizing predefined features reveal that supervised layer-wise trained DCNNs outperform these models. They surpass previous benchmarks on the CMATERdb 3.1.3.3 dataset, achieving an excellent error rate of 9.67% and a recognition accuracy of 90.33%. This represents a remarkable improvement of over 10%. Islam, Khalid Amirul, et al. [4] focuses on understanding and translating collected signs into Bangla. Using image processing and machine learning, this involves the detection and identification of road signs. To match road signs with a database, a template matching algorithm is used. The matched signs are then translated into Bangla or English, depending on the user's selection, and synthesized as audio output. The system consists of modules for detection, identification, and voice synthesis, each of which is created to carry out its specific role successfully and efficiently. Future developments are predicted, and continuous work is being done to incorporate more features in order to reach a 90% accuracy rate for detection. Sen, Ovishake, et al. [5] emphasized the paucity of thorough analyses of recent advancements in BNLP (Bangla Natural Language Processing) tools and techniques. Information Extraction, Machine Translation, Named Entity Recognition, Parsing, Parts of Speech Tagging, Question Answering System, Sentiment Analysis, Spam and Fake Detection, Text Summarization, Word Sense Disambiguation, and Speech Processing and Recognition are just a few of the 11 categories that the study analyzes 75 BNLP research papers into. The research includes publications that were published between 1999 and

2021, with a focus on articles that were published after 2015, which made up 50% of the total. The paper also reviews various datasets, tackles restrictions, and evaluates current and future developments in BNLP. It also examines classical, machine learning, and deep learning methodologies. Rahman, MM Shaifur, et al. [6] introduced a BLPRS system based on convolutional neural networks (CNNs) that provides better accuracy and is suited for a number of applications, such as roadside assistance, automatic parking lot management, and the identification of car license status. In addition, the study provides a brand-new, standardized database created especially for BLPRS. The implemented system, which has been trained on a large number of samples, achieves an excellent testing accuracy of 88.67%, making it the most accurate in this situation. Das, Sunanda, et al. [7] proposed a hybrid approach that incorporates numerals and alphabets for the automatic recognition of Bangla Sign Language (BSL). A convolutional neural network with deep transfer learning and a random forest classifier are combined in the model. Two open-access, extensive datasets for BSL called "IsharaBochon" and "Ishara-Lipi" are used for performance evaluation. The research also introduces a backdrop elimination technique designed to eliminate superfluous characteristics from sign images. The system obtains outstanding results with accuracy, precision, recall, and f1-score values of 91.67%, 93.64%, 91.67%, and 91.47% for character recognition and 97.33%, 97.89%, 97.33%, and 97.37% for digit recognition, respectively, after using this background elimination strategy. The experimental analysis supports the viability and efficacy of the suggested BSL recognition system. Khan, Rizwanul Haque, et al. [8] addressed the dearth of studies and publicly accessible datasets for traffic sign detection in Bangladesh. A dataset of 6775 photos from 27 different traffic sign classes has been assembled by the researchers. This dataset comprises difficult samples that reflect real-world circumstances, including as small-sized signs, obscured signs, different lighting settings, and hazy conditions. Modern object identification architectures were used, and YOLOv5x emerged as the top model with a mean Average Precision (mAP) score of 92%, acting as a benchmark. The model's robustness in real-world situations was further validated by testing it on 2000 photos of non-traffic signs as part of a thorough performance analysis on the curated dataset. Rabby, AKM Shahariar Azad, et al. [9] presented an innovative attempt to recognize different categories of handwritten characters in Bangla, including basic letters, numerals, modifiers, and compound characters. Due to its many uses and function in digitizing and preserving historical records and information, handwritten character recognition is a topic of great interest. Character recognition in Bangla is extremely difficult because every writer has a different writing style and every character is different in size and shape. The 50 fundamental letters, 10 digits, 10 modifiers, and 52 frequently used compound characters in Bangla script are all recognized by the EkushNet model to help with this problem. A considerable improvement in Bangla character recognition was made by the model, which was trained and validated using the Ekush dataset and cross-validated with the CMATERdb dataset. The model achieved outstanding recognition accuracy of 97.73% for Ekush and 95.01% for CMATERdb. Huda, Mohammad Nurul,et al. [10] discussed the creation of a system for identifying and translating traffic directives found in naturally occurring images with Bangla text. To extract and translate information from images, the system combines techniques such as image processing, machine learning, optical character recognition (OCR), and machine translation. The workflow of the system consists of three primary steps: machine translation, post-processing using a language model, and text extraction from the image. This method makes it possible to automatically extract and translate Bangla text from photos. Abdullah, Sohaib, et al. [11] presented a comprehensive real-time Bangla license plate identification system that can handle challenging real-world scenarios with large variability. The system incorporates a cutting-edge technique for recognizing license plates, resulting in an extensive, end-to-end deep learning-based Automatic License Plate Recognition (ALPR) system. A dataset of 1,500 unique photos of Bangladeshi vehicle license plates was gathered, and the photographs depicted varied real-world situations. The YOLOv3 algorithm was used for license plate localization and digit recognition, obtaining over 85% Intersection over Union (IoU) in digit recognition. Additionally, a deep convolutional neural network (CNN) based on ResNet-20 was trained on a dataset of more than 6,400 Bangla characters from scenes, and it was able to recognize Bangla characters on license plates with 92.7% accuracy. Sumit, Sakhawat Hosain, et al. [12] presented a complete deep learning method for identifying continuous Bangla speech, particularly in noisy settings. Advanced deep model architecture and data augmentation approaches increase the model's robustness. Internal and openly accessible datasets are used to evaluate the model. Character Error Rates (CER) of 10.65% for clean read speech and 34.83% for noisy speech on the Babel dataset demonstrate remarkable results on both clean and noisy speech data, establishing a state-of-the-art performance in continuous Bangla speech recognition. CER rates of 12.31% for clean speech and 9.15% for noisy speech were obtained for the internal dataset. Sharmin, Riffat, et al. [13] addressed the problem of Bengali spoken digit classification and emphasizes the significance of taking into account important factors that determine speech characteristics, such as dialects, gender, and age groups. One or more of these factors were frequently ignored in earlier efforts in this field. The research offers a deep learning method that takes into consideration all of these factors for classifying spoken Bengali digits. The suggested method successfully recognizes Bengali spoken digits across diverse dialects, genders, and age groups with an astounding accuracy rate of over 98% using a convolutional neural network (CNN).Ahmed, Md Tofael, et al. [14] utilized both machine learning and deep learning techniques to create a model for detecting cyberbullying in texts written in Bangla and Romanized Bangla. 5000 Bangla, 7000 Romanized Bangla, and a mixture of 12000 Bangla and Romanized Bangla texts were divided into three separate datasets from social media content. The preprocessed datasets were utilized to train several algorithms. Convolutional Neural Network (CNN), a Deep Learning algorithm, produced the best results in terms of performance, with an accuracy of 84% for the Bangla dataset. The Machine Learning Technique Multinomial Naive Bayes fared best, reaching accuracies of 84% and 80%, respectively, for the Romanized Bangla dataset and the combined dataset. The algorithms were compared in the study based on their accuracy, precision, recall, F1-score, and ROC area. Abedin, Zainal, et al. [15] presented a system for the detection and identification of traffic signs. Using fuzzy rules based on hue and saturation values in the HSV color space, the system divides the region of interest (the sign area) in the detection step, followed by post-processing to remove undesired regions. A classifier trained on SURF feature descriptors allows for the recognition of traffic signs. The system was put to the test using offline road scene photographs taken in various lighting situations, showing strong detection and acceptable recognition rates. The ANN model outperformed other classifiers including Support Vector Machine, Decision Trees, Ensembles Learners (Adaboost), and K-Nearest Neighbor when performance was measured using cross-entropy, confusion matrix, and ROC curves. The results show that the ANN classifier using SURF descriptors has an overall correct classification rate of 97%. Ahmad, Istiak, et al. [16] utilized both manual and automatic labeling techniques to investigate various machine and deep learning methods for news classification in the Bangla language. Along with several text embedding models, the machine learning techniques used in this study include Logistic Regression, Stochastic Gradient Descent, SVM, RF, and KNN. Additionally, word embedding models are combined with deep learning algorithms including Long Short-Term Memory, Bidirectional LSTM, Gated Recurrent Unit, and CNN. The authors produce a sizable dataset called Potrika that includes 664,880 news stories in eight categories from well-known Bangladeshi news sources, making it an important tool for studying the Bangla language. The results show that for manually labeled data, GRU and Fasttext obtain the maximum accuracy (91.83%), while KNN and Doc2Vec perform admirably with 57.72% and 75% accuracy for single-label and multi-label data, respectively, when utilizing automatic labeling methods. These discoveries are anticipated to make a substantial contribution to studies on the Bangla language and beyond. Mahal, Somania Nur, et al. [17] analyzed contemporary deep learning developments, particularly as they relate to feature extraction from image patches. It proposes a novel method that blends supervised feature learning with a multilayer convolutional neural network (CNN), enhancing system performance and improving text recall rates within images. The approaches mentioned are used to develop a learning model that can read handwritten and scene text in natural photographs in both Bangla and English utilizing both simulated and real-world data. The method uses an unsupervised deep belief network of 60 classes, including 50 basic letters and 10 Bangla numbers, and it achieves a remarkable recognition accuracy of 90.27%. Bhowmik, Nitish Ranjan, et al. [18] focused on Sentiment Analysis (SA) in the Bangla language. Starting with two Bangla datasets, it applies normalization, tokenization, and stemming techniques to build a lexicon data dictionary (LDD) specifically designed for sentiment analysis in Bangla. To determine sentence polarity by taking into account part-of-speech tagged words and special characters to provide word and sentence scores, a unique rule-based system called Bangla Text Sentiment Score (BTSC) is introduced. In order to extract sentiments from the two Bangla datasets, the BTSC method and the LDD are both used. Using the datasets and accompanying BTSC scores as input, two feature matrices are created using the term frequency-inverse document frequency (tf-idf) technique. The success of the BTSC technique for Bangla SA is highlighted by the fact that supervised machine learning classifiers are used to assess these feature matrices. Support Vector

Machine (SVM) achieved the maximum classification accuracy of 82.21%. Tajrean, Shaharat, et al. [19] emphasized the most current developments in AI, particularly the superiority of deep neural networks over more conventional feature-based machine learning techniques. It highlights, particularly in the context of Bengali handwritten number detection, the efficacy of region proposal networks (RPN) within deep neural networks for object detection. By utilizing deep neural networks and a painstakingly created, unbiased dataset, the authors present a very reliable approach for identifying handwritten Bengali digits. Surprisingly, the system yields cutting-edge outcomes, surpassing earlier work by a considerable margin when evaluated with real-world datasets, and achieving an amazing overall detection accuracy of 97.8%. The system is also developed with Python and Google's TensorFlow framework, enabling accessibility and usability for a larger audience, and it enables real-time processing capabilities at about 35 photos per second using GPU acceleration. Saha, Sourajit, et al. [20] proposed a brand-new neural network architecture with the goal of effectively learning filters with fewer parameters and a shorter learning period. In addition, a method for choosing a particular network section that nonetheless has equivalent learning capabilities to the complete network is presented in the paper. This technique ensures the neural network's impartiality with regard to viewpoint while improving classification accuracy. With an amazing accuracy rate of 97.21%, the suggested model performs as a thorough image classifier for different Bangla handwritten letters and numerals. The report provides compelling findings and solid data to support its approaches.

2.3 Comparison between existing works

In our comparative analysis and summarization process of the literature, various milestones on deep learning methodologies for Bangla Road sign detection have been acknowledged. For instance, Banik et al. [1] have focused on feature vectorization and neural network training for achieving accurate results in recognition procedures while accurately Alom et al. [2] have pointed out that the CNN with dropout and filter improvements has a greater impact on the recognition of handwritten Bangla digits. This recent work of Roy et al. [3] employs the supervising layer-wise training for modelling and recognizing compound characters and reports improved results. In contrast, Rahman et al. [6] produce convincing evidence of surpassing CCTV-BPLPR’s conventional techniques utilizing purely CNNs trained with a large dataset Bangla license plate. Cuccinello (2018) and Shrestha et al. (2018) among other previous studies further affirm that deep learning especially CNN derivatives hold a strong capability in handling a range of difficult Bangla image recognition that can translate to improvement in real-life traffic controls and security.

TABLE 2.3 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL	Author Name	Used Algorithm	Best Accuracy
1.	Roy, Saikat, et al.	DCNN	90.33%
2.	Rahman, MM Shaifur, et al.	CNN	88.67%
3	Das, Sunanda, et al.	CNN with transfer learning and RF classifier	91.67%
4	Khan, RHaque, et al.	YOLOv5x	92%
5	Rabby, AKM S Azad, et al.	CNN with background elimination	91.67%
6	Abdullah, Sohaib, et al.	YOLOv3, ResNet-20	92.7%
7	Ahmed, Md Tofael, et al.	Convolutional Neural Network (CNN)	84%
8	Ahmad, Istiak, et al.	Deep Learning algorithms	91.83%
9	Mahal, Somania Nur, et al.	Convolutional Neural Network (CNN)	90.27%
10	Bhowmik, NRanjan, et al.	Rule-based system, SVM	82.21%

2.4 Open Issues

The domain of interest concerns improving the performance of Bangla Road sign real-time detection of road signs for navigation using modern advanced deep learning-based approaches. Due to change in traffic density and type of roads in Bangladesh, it becomes highly significant and urgent to identify the signs accurately and efficiently for the improvement in road safety and management. Using CNNs and other advanced developments in the advanced process algorithms, the goals of this study are to come up with models that could be very effective in the classification of different Bangla Road signs under different environmental conditions. It includes the broad area of data augmentation, model optimization as well as comparative study of some of the most advanced DL models that are in use in the current world and hope to achieve higher levels of accuracy in traffic regulation and safety measures that have normally been achieved by classical methods.

2.5 Summary

There are many challenges observed for real-world Bangla Road sign detection using DL methods. The current limitation is the differences in road signs, due to factors such as lighting, weather conditions, and occlusion. The following are some of the challenges that are experienced; there are few annotated datasets available in the Bangla which only contains the road signs and that too in limited amount which requires a colossal amount of data collection and annotation. Furthermore, the real-time reconfiguration of deep learning architectures on energy-restricted devices should also still be addressed. Solving these problems necessitates having an efficient image preprocessing approach, proper data augmentation schemes, and constant enhancement of the model. These challenges will improve the effectiveness and practicality of deep lecture models in actual-life settings, thus improving traffic systems to provide safer traffic.

CHAPTER 3
METHODOLOGY

3.1 Overview

The research subject revolves around training a model of a deep learning algorithm for the detection of Bangla Road signs that could ensure improved traffic safety and management in Bangladesh. Consequently, instrumentation is made through the use of the most advanced CNNs that include VGG16, Xception, DenseNet201, and ResNet50 as well as developing a new CNN. All these models will be trained and tested on a rich Bangla Road sign dataset that will incorporate a variety of environmental conditions as well as different sign variations. Datasets and objectives of the research There are three important approaches of the research in terms of dataset and objectives: Advanced image processing techniques Data augmentation High accuracy in real-time road sign detection This will help in progressing with the particularized vision that is likely to be apprehended by utilizing automated schemes for traffic signs recognition for Bangla-scripted settings.

3.2 Proposed Methodology

The systematic approach for the identification of Text Based Bangla Road Sign through the use of deep learning is as follows: Every stage is carried out to the following in order to invent an accurate and strong detection ability. Steps in the Proposed Methodology:

Data Collection:

Images of Bangla Road signs were collected across Dhaka, Bangladesh. Using digital cameras and smartphones, images were captured under different lighting, weather, and traffic conditions to simulate the challenges faced in practical environments.

Data Labeling:

The Images of Bangla Road signs were collected as dataset, and these Images were annotated along with bounding box and categorized by labeling them in 11 different class of road signs. This labeling process enabled deep learning models to attain the desired recognition and classification of the road signs.

Image Augmentation:

As a result of implementing the methods I have described below, the size and quality of the Bangla Road sign dataset were increased. Such methods included but not limited to rotation, flipping, scaling and changes in brightness/contrast. Augmentation was designed to enhance the variations of the provided dataset and the former was comparable with the latter in terms of its performance on the basis of deep learning models regardless the environmental or lighting conditions that can be met in practice.

Visualization:

Visualization in this case means representing and interpreting of Bangla Road signs dataset through graphics. Graphic types like bar plot, histogram, and scatter plot can apply to represent the distribution of road sign classes, image feature like size or aspect ratio and other statistical properties. People use visualization to familiarize themselves with the properties of the dataset, search for possible biases or unbalances, or define how to preprocess data to increase the performance of models afterwards.

Implementing CNN:

The Bangla Road sign detection uses the following CNN architecture Convolutional Layer: Several layers are responsible for extracting features from the images input. After convolution and pooling processes, the feature maps are flattened and fed through dense layers for classification, also dropout and batch normalization are utilized in this step for regularization and stabilization purposes. Adam optimizer used in training process and categorical cross-entropy loss used for its training, the model is expected to gain high accuracy and better recognition on the Bangla Road sign from a wide range real image. To show the effectiveness of the proposed model, the following items are to be considered: The proposed custom CNN: This model is designed for Bangla Road sign detection, while it tries to maintain both computational time and accuracy. Small filters and batch normalization procedures along with ReLU nonlinearity and residual connections are used to strengthen the features extraction process and gradient propagation. This design makes it possible for the model to capture the necessary features of Bangla Road signs and classify them under any condition that may arise in the real world.

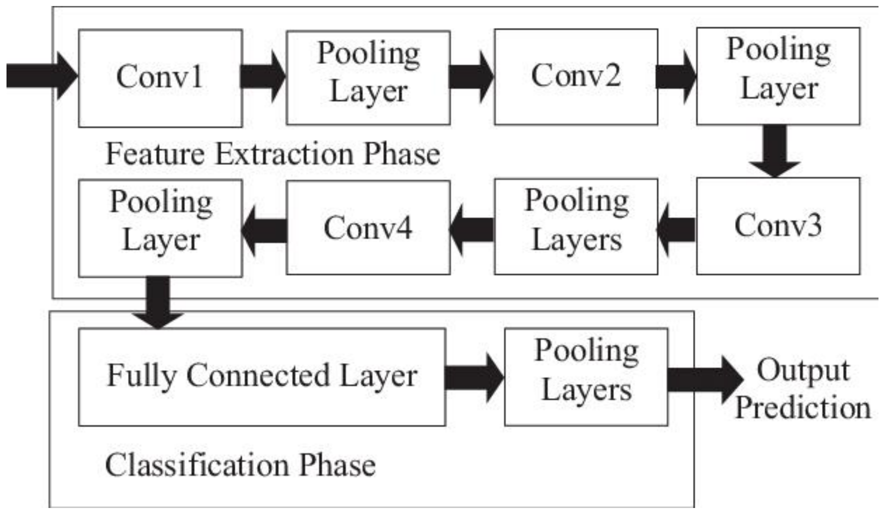

Figure 3.1: CNN Architecture S. V. Militante et al.2019[21]

Model Selection:

A process of selecting suitable model from a pool of models for Bangla Road sign detection involves selecting the most suitable architecture. Some of these considerations include the capacity of the model to address complex features within the features, and the capacity of the model to handle big data sets with the help of available metrics including accuracy, computing resource utilization, among others. In fact, evaluation criteria also include the degrees to which a model can be resilient to different environmental configurations and the extent to which the model is capable of generalizing from one application to other. These aspects include network depth, number of learnable parameters, receptive fields, input image size, number of layers, and Number of trainable parameters and models such as VGG16, Xception, DenseNet201, ResNet50 and customized CNN are used to assess them to identify which model is optimal for Bangla Road signs detection and classification in practical settings such as real road scenarios. In given below I am shortly described about those models:

Xception

Xception is particularly useful in this study since depth wise separable convolutions are incorporated by the model, which makes computations faster and offers accuracy. For example, its architecture consists of 36 convolutional layers with the usage of residual connections, as this would enable better feature extraction. For this reason, Xception proves to be highly suitable for identifying the Bangla Road signs in various and complex environments.

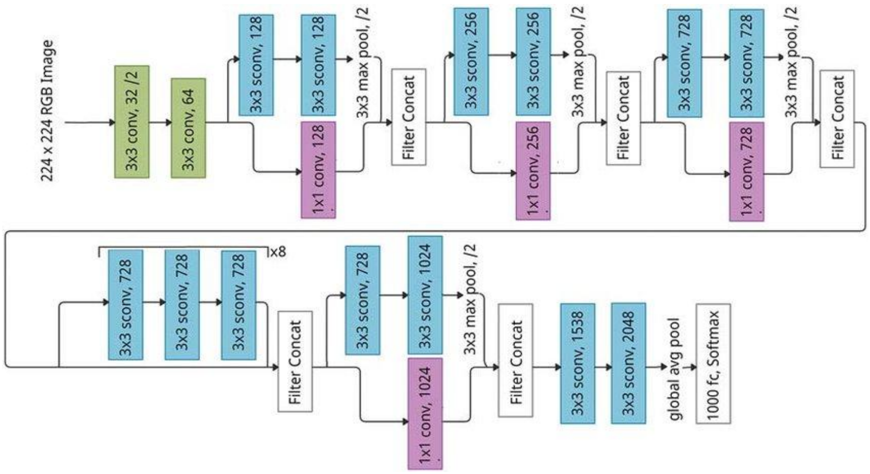

Figure 3.2: Xception Architecture K. Srinivasan et al 2021 [22]

ResNet50

ResNet50 is particularly useful for the present study due to its residual learning approach, which makes it easy for training very deep neural networks where the problem of vanishing gradient is likely to occur. The layers in ResNet50, which is 50 adequately extracts multiple-level details in Bangla Road signs. MMV does not allow for the information loss that is possible with regular connections through pooling layers; skip connections help the model retain high accuracy and resistance to various and intricate detection tasks.

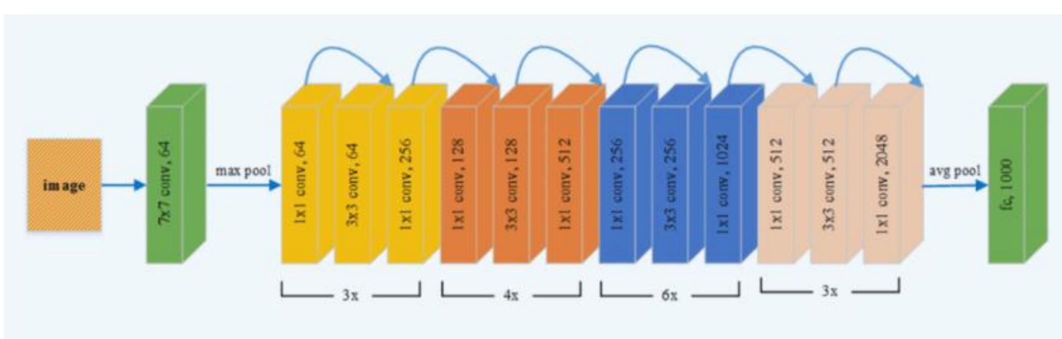

Figure 3.3: ResNet50 Architecture S. Albahli, 2022 [23]

DenseNet121

The choice of DenseNet201 is more knowledgeable given its dense connection mechanism that keeps the reuse of feature maps and gradient flow efficient. This architecture of 201 layers, made doubly connected, means that each layer receives inputs from all the layers that come before it and allows for the discouragement of the vanishing gradient problem. Due to these characteristics DenseNet201 could be used for Bangla Road signs detection with high accuracy rate and confidence.

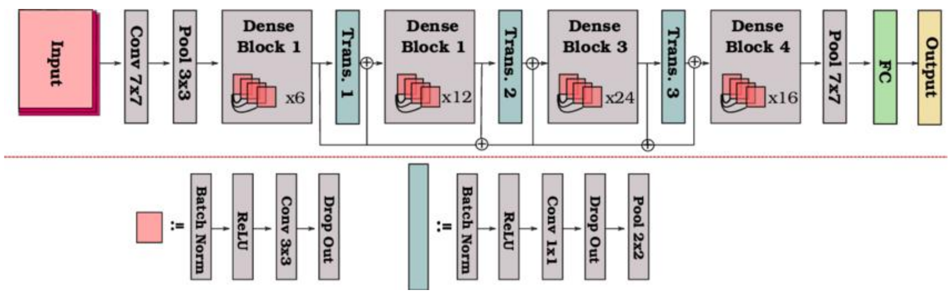

Figure 3.4: DenseNet121 Architecture Radwan, Noha.2019 [24]

VGG16:

This research especially utilizes VGG16 is most suitable because it is relatively simple, deep enough, and suitable for the detection of the features of Bangla road signs. Its architecture – 13 convolutional layers with relatively limited kernels (3×3) and the rest of the fully connected layers allows for high accuracy and feature learning, making DCNet well-fitted to precise image recognition in various environments.

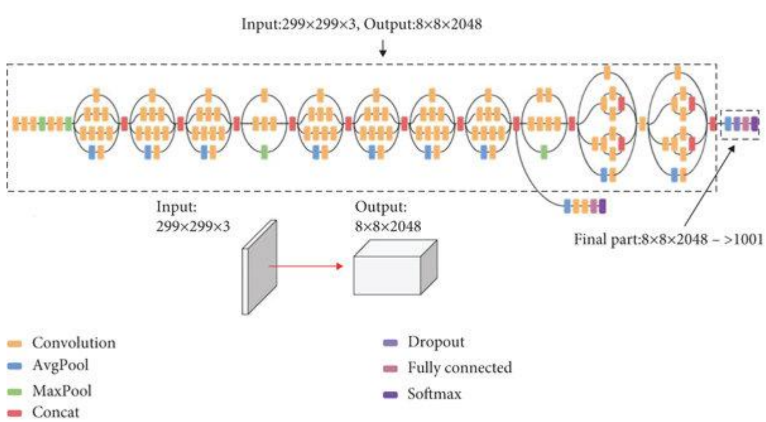

Figure 3.5: VGG16 Architecture S. Ramaneswaran 2021 [24]

Training and Validation:

For training and validating the CNN architecture for Bangla Road sign detection, initially we split the data into the training and validation 80/20. The model is then trained on the training set through some strategies such as stochastic gradient descent and the Adam optimizer to minimize the categorical cross-entropy loss. In assessing performance during the training process, accuracy and so forth are computed using the validation set to determine the model's ability to generalize beyond the training data. The hyperparameters of the model, the network structure, and data augmentation techniques are optimized based on the validation set results until a suitable level of accuracy and stability. This iteration process helps to develop the CNN model capable to classify Bangla Road signs in different real-time environment.

Test Model:

The trained CNN model of Bangla Road sign detection entails assessing the test time loss and accuracy on different Bangla Road sign images that were not used during the training or validation process. This dataset helps control the model's capacity to predict on unseen data and mimic performance in actual applications. The test dataset holds the Bangla Road signs images, and the labels under which each image has been categorized are predicted by the model. To compare the efficiency of the model for enabling recognition of road signs under different situations, accuracy, precision, recall, and F1-score are used measurements. From the results obtained from testing, it can be asserted that the proposed CNN model is reliable and works effectively for real life Bangla Road sign detection.

Model Evaluation:

The model evaluation for Bangla Road sign detection aims at comparing the performance metrics of a CNN on the test set of images, which includes accuracy, precision, recall, and F1 score. The evaluation assesses how the model performs when applied on never-seen data, thereby revealing the ability of the model to classify other Bangla Road signs under real-world situations.

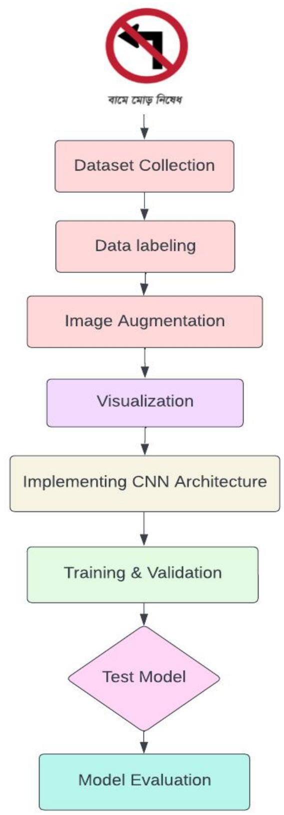

Figure 3.6: Work Flow

3.3 Hardware/ Software Requirement

For implementing the CNN model of Bangla Road sign detection, there are pre-requisites and tools needed. Firstly, that is why it is crucial to have a large number of images in the useful database with annotations that includes various classes of road signs. High end computers with relatively large processing capabilities usually in the form of GPU are required to perform the required calculations needed for training the deep learning models. There is model development and training of the models using such software development tools like TensorFlow or PyTorch which are equipped with deep learning libraries and optimization tools. Further, data preparation techniques namely image augmentation, image normalization and furthermore, splitting of dataset into training and validation data sets are performed for fine tuning model performance and reliability. The validation step means constant Tweaking of these parameters so as to achieve the highest model accuracy and effectiveness at runtime as well as during the development of the model.

3.4 Project Management and Financial Analysis

The project will be organized in stages, including data collection and preparation, model selection, training, and performance assessment. In each of the phases a timeline will be set with regard to the various milestones with a view of ensuring that there is some form of accountability in the achievement process. For development, a specific team that consists of data scientists, agronomists, and software designers will assess the reinforcement of the domain knowledge with professional skills. The gains obtained from these interactions will be prompt response to problems and effective communication, as a result of weekly meetings and updates. This budget is for Collecting Data, purchasing hardware, including high-resolution cameras for data gathering and computational equipment (GPUs) for training deep learning as well as software licenses. Furthermore, there will also be expenses for the basic consulting and personnel costs, and consultation with experts. Cost leadership will be maintained to ensure that there is optimum control of costs.

TABLE 3.4: PROJECT MANAGEMENT TABLE

Work	Time
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

3.5 Summary

The paper presents a deep learning solution and its assessment on CNN frameworks for classifying Bangla road signs. Bangla road sign images of 11 different categories were collected and post processing was done in order to attain necessary uniformity and authenticity of the data set. Realization of various CNN architectures included, but not limited to, VGG16, Xception, DenseNet201, ResNet50, and a specially devised CNN architecture utilizing TensorFlow together with Keras. All the computations were done on GPUs to hasten the fast-forwarding of the models. For each of the models, the evaluation was done according the accuracy and other significant factors. The principles of the custom CNN were aimed at overcoming the problems that arise when perceiving the Bangla script language and improving the identification of textual road signs. Taking this into account, comparative analysis intended to determine the most effective model that will help to create further developments in the sphere of ITS with focus on Bangla-speaking countries.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

For implementing the CNN model of Bangla Road sign detection, there are pre-requisites and tools needed. Firstly, that is why it is crucial to have a large number of images in the useful database with annotations that includes various classes of road signs. High end computers with relatively large processing capabilities usually in the form of GPU are required to perform the required calculations needed for training the deep learning models. There is model development and training of the models using such software development tools like TensorFlow or PyTorch which are equipped with deep learning libraries and optimization tools. Further, data preparation techniques namely image augmentation, image normalization and furthermore, splitting of dataset into training and validation data sets are performed for fine tuning model performance and reliability. The validation step means constant Tweaking of these parameters so as to achieve the highest model accuracy and effectiveness at runtime as well as during the development of the model.

4.2 Train Model/ Prototype Design

The training model for Bangla Road sign recognition involved implementing multiple CNN architectures: VGG16, Xception, DenseNet201, ResNet50, and a new designed CNN. Training and test data were prepared in such a way that the selected dataset of 11 Bangla Road sign categories was corrected into training and testing. All the models were implemented using TensorFlow and Keras frameworks with tuning done on hyperparameters. Training was done using GPUs so that the amount of computation done was efficient and fast. The proposed specific custom CNN architecture is envisaged to tackle some of the peculiarities of Bangla script by enhancing the number of layers and the fine-tuning processes. Since the accuracy, the precision, recall, and F1 score metrics were used, the accuracy of 96 was achieved by the custom CNN. For this task, the tool was most effective with 41% of the overall format polishing work completed.

4.3 System Design/ Model Evaluation

This work describes the challenges and the system framework for Bangla road sign recognition which is preceded by data procurement and ended with the assessment of the model. The data set contains 11 Bangla road sign classes' images and are standardized for analysis. EEG Features of Multiple CNN structures, such as VGG16, Xceptio, Dense 201, ResNet 50, and a customized CNN were accomplished by TensorFlow and Keras. All the models had their training done on GPUs to make sure that it would be able to compute problems faster. Model evaluation was done by the process of division of the dataset into a training set and a testing set. Each model was evaluated using performance indicators consisting of accuracy, precision, recall, and F1 score. The assessment also discusses the future of the proposed custom CNN and offers findings for future development and implementation in the new ITS in Bangla-speaking countries or areas.

4.4 Summary

The chapter on implementation explains the methods regarding the creation and application of multiple CNN architectures to Bangla Road sign recognition. Model construction and training process include TensorFlow and Keras and the selected models are VGG16, Xception, DenseNet201, ResNet50, and a customized CNN model; here, the dataset is 11 Bangla Road Sign categories. Training speed and efficiency was also promoted via the use of GPUs. The organs Hell custom CNN was explicitly created to solve the characteristics of Bangla script in road signs. There was strong focus on hyperparameters setting and convergence to seek the best performance in the implementation. The models' performance was assessed based on such parameters as accuracy, precision, recall, and the F1 score; it is pertinent to note that the proposed custom CNN showcased an accuracy of 96%. 41%. This chapter shows how the theoretical knowledge and general concept of Convolutional Neural Networks can be put into practice for the Bangla Road sign recognition for real application.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

For this project developed on Google Collab, which utilizes GPU resources from the cloud to work well in handling operational deep learning demands. The dataset, which included both normal and augmented Bangla Road sign images across eleven classes, was kept in the format depicted above and was stored in Google Drive for better organization. For data manipulation, data visualization and model evaluation, we used TensorFlow and its prerequisite libraries like NumPy and Pandas, Matplotlib and Seaborn. The division of the dataset was done using function train_test_split available in sklearn so that there is an 80:20 division between training and testing data for a significant model training and evaluation. Preprocessing images is done by using image data generators from tensorflow's keras. This preprocessing module also played a role in loading data, preprocessing it, and augmenting the data, which is vital and useful in improving the model generalization. The model was designed with the help of CNNs, used TensorFlow as well as Keras APIs, and incorporated transfer learning in order to use initial weights. In this setup, it was possible to maintain comparable levels of reproducibility, scalability across individual experiments, and the appropriate allocation of computational resources during the experimental stage.

5.2 Experimental Result

The experimental outcomes are evidencing the feasibility and benefits of the proposed Bangla Road sign detection system. Using CNN constructed from the first layer and data that have been augmented, the model yielded an average accuracy of 96.41% on the test dataset reducing the overall accuracy of the algorithm from the training phase. Comparing the accuracy of the various deep learning models; namely the VGG16, Xception, DenseNet201, and ResNet50, it was observed that the VGG16 and Xception architectures returned the maximum accuracy of 99. 51% for the effectiveness of MButterflies largely indicates their suitability for this particular purpose. It was observed that matrices and reports for confusion also indicated good performance in several classes of road signs with little cross-over errors. The few demonstrated results in this paper coincide well with the objective of deep learning methods in identifying and categorizing Bangla Road signs and thereby paving the way for future developments and implementations in traffic control and safety systems.

In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

Result of Experiment 1: CNN

The proposed CNN model that was trained to address the Bangla Road Sign Dataset performed remarkably well on the test set as an indication that the work as specialization of CNN models is efficient in the identification of road signs. This model reached about 96.41% accuracy, signifying the fact that it effectively managed to categories a huge chunk of the test images. Precision was at 96.40% and recall also was at the similar percentage 96.41% respectively because the model is capable of fine-tuning its parameters to zero in on the relevant cases and because the precision coefficient recognizes instances that are genuinely positive. The F1 score was estimated to be 96.40%. This is a further proof because the chosen score is based on the balanced measure of both, precision and recall. These findings underscore the flexibility and efficiency derived from the proposed customized CNN on learning possible difficulties of Bangla Road signs and its potential for actual implementation.

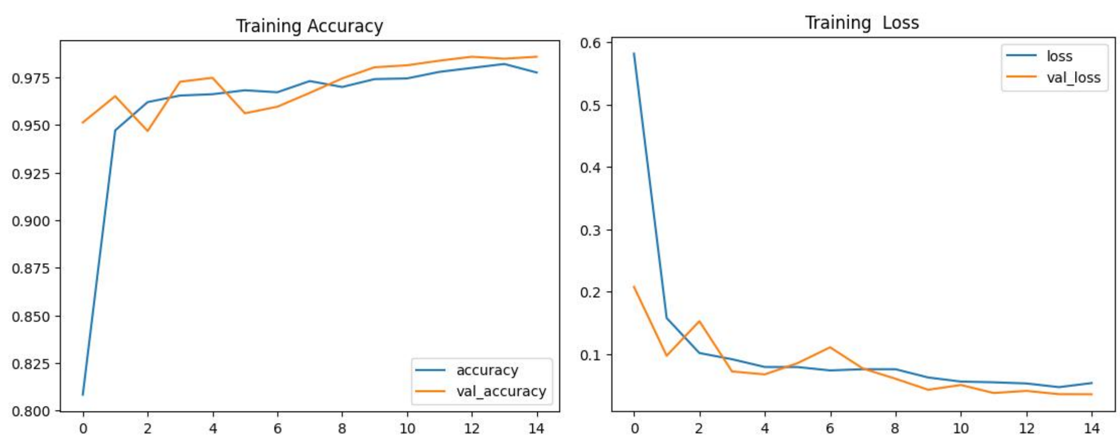

Figure 5.1: Training and validation accuracy and loss over the epochs (CNN)

Figure 5.1 shows the plots The trained CNN model in Bangla was able to achieve a performance of 97% on the test set, proving the efficiency of the proposed model for Bangla Road Sign detection and classification. The model achieved an accuracy of 96 percent and this is an indication of the high degree of closeness of the results to the actual. 41%, which means that the probability of separating the test images correctly was very high, which is 41%. Hence for the proposed model, precision and recall values were measured to be 96%. 40% and 96. The result values are calculated as follows: precision, 0. 803 or 44% currently, and recall, 0. 410 or 41% respectively, which prove the model's aptness for constant identification of related cases and responsibility for true positive findings. The graphical representation of the evaluation criteria shows that F1 score stands at 96. As we can observe, the chosen approach of using F1-measure, which is the harmonic mean of precision and recall with the value 40%, further validates the overall performance of human-driven model that is oriented both on precision and recall at the same time. Returning to the study of Bangla Road signs, the results emphasize the effectiveness and efficiency of the customized CNN in terms of capturing the essence of the images and addressing the challenges and variations inherently found in traffic systems that are closely related to autonomous driving systems.

In below Figure 5:2 describing the confusion matrix of CNN:

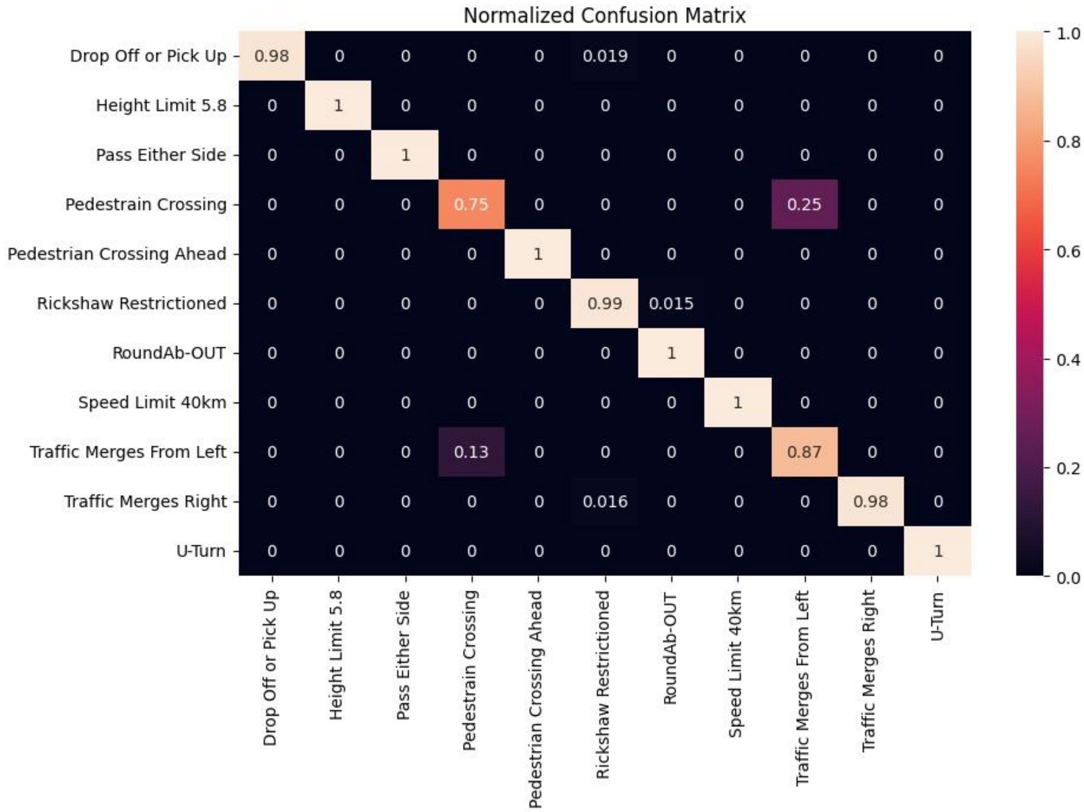

Figure 5.2: Confusion Matrix (CNN)

Figure 5.2 shows the confusion matrices, it can be inferred that the customized CNN model performs well when predicting Bangla Road signs in 11 classes. All but three categories, namely ‘’Road Narrows’’, ‘’Children’’ and ‘’School Zone’’, had an accuracy of at least 98 percent, which would mean that the model is effective in classifying such signs with almost no mistake. But, one modality has been less accurate and confused between “Pedestrian crossing” and “Pedestrian crossing ahead” with a high misclassification rate of 25%. Likewise, the ‘Traffic Merges from Left’ class had relatively high misclassification rate where the signs were misclassified to ‘Pedestrian Crossing Ahead’ with a rate of 13%, other minor misclassification include; ‘Rickshaw Restricted’ and ‘Traffic Merges Right’ but they were low. Ordered by whole points and 10 Paired samples McNemar testing, the confusion matrix demonstrates high accuracy and efficiency of the model while revealing its potential enhancements to distinguish similar road signs visually.

Result of Experiment 2: Transfer Learning Model

Xception:

The performance of the Xception model can be praised as outstanding in identifying Bangla Road signs; the accuracy is nearly 99.51%. Even on the test set the accuracy is high, reaching the precision, recall and the F1 score, more or less are approximately equal to 0. 995 Such a high coefficient confirms the stability of ten indicators showing the reliability of the model. The qualitative analysis done on a class-wise basis shows very high performances across most of the classes with most of the classes reporting 100% Precision, Recall, and F1 score. Only two out of all the classes, "Drop Off or Pick Up" and "U-Turn", slightly deviate from the average recall of 0. 96 while the latter has a precision of 0. 95, indicating minor misclassifications. Thereby, the confusion matrix and classification report show that the proposed model achieved high performance, even in determining different Bangla Road signs where visual distinctions between signs are sometimes inconspicuous to the human eyes. This high and balanced performance in all the metrics reveals the efficiency of the Xception model toward its real-world uses in traffic control and other auto-mobile applications for Bangla Road sign identification. In below Figure 5:3 describing the confusion matrix of Xception:

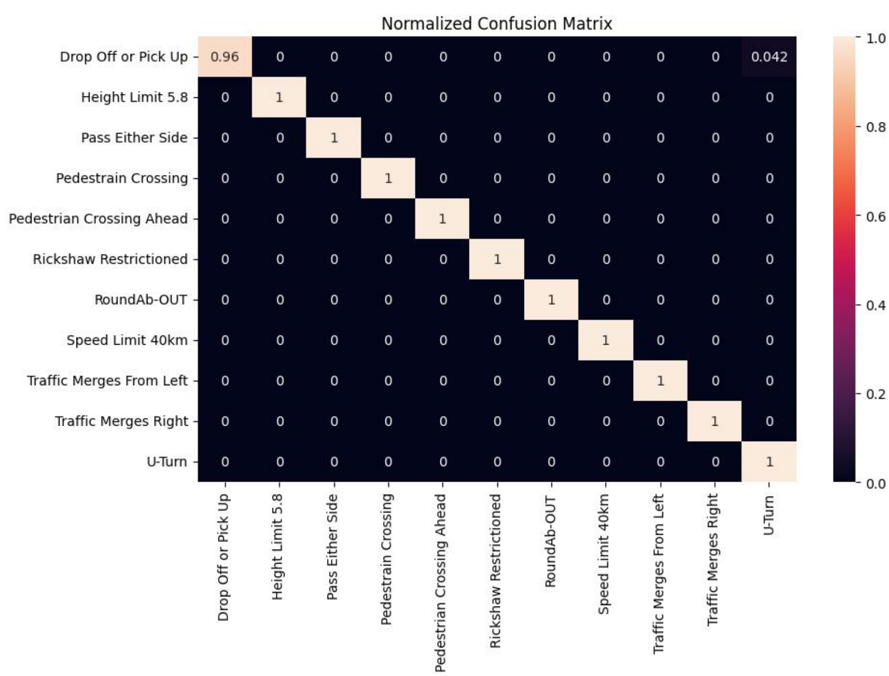

Figure 5.3: Confusion Matrix (Xception)

Figure 5.3 shows the normalized confusion matrix illustrates the performance of a multi-class classification model, likely for traffic sign recognition. The matrix reveals that the model achieves near-perfect classification accuracy for most traffic sign categories, as indicated by the value of 1 along the diagonal for almost all classes. Specifically, classes such as 'Height Limit 5.8', 'Pass Either Side', 'Pedestrian Crossing', and several others show perfect classification with no misclassifications. The only notable exception is the 'Drop Off or Pick Up' class, which has a true positive rate of 0.96 and a minor misclassification rate of 0.042, indicating that a small percentage of 'Drop Off or Pick Up' signs were incorrectly predicted as another class. Overall, the confusion matrix highlights the model's robustness and high accuracy, with very few errors in classification.

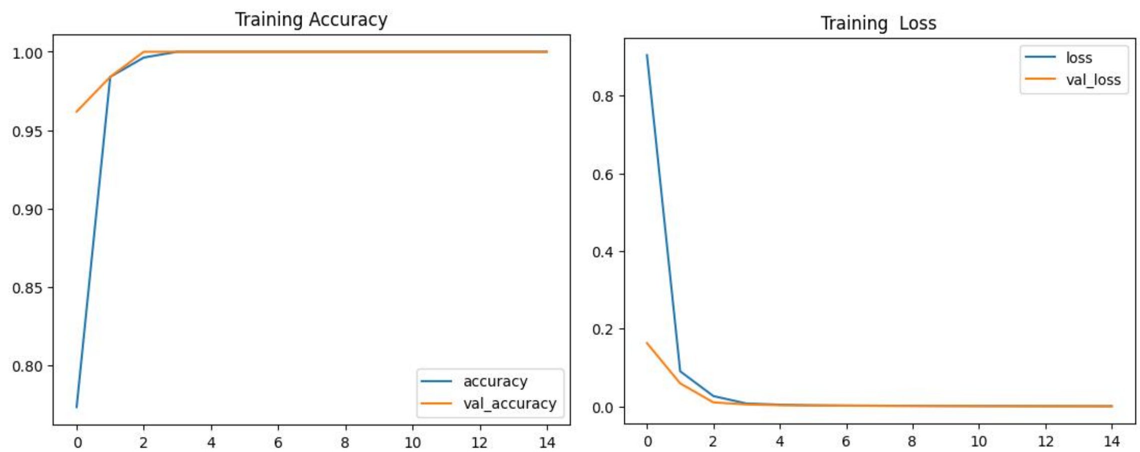

Figure 5.4: Training and validation accuracy and loss over the epochs (Xception)

Figure 5.4 shows the training accuracy and loss of the Xception model show very good results as illustrated in the two graphs below; The next plot on training accuracy offers quite a similar pattern and learns that both the training and validation accuracy promptly rise almost hitting 100% with little oscillations. If the loss decreases significantly and the values of accuracy and/or other model’s parameters on the validation dataset grow, it means that the model learns and generalizes well. After epoch 1, accuracy fluctuates only slightly, which indicates the model’s quick convergence. The training loss plot augments this by depicting a sharp decrease in the beginning and gradually approaching the near-zero range in the first few epochs. Training loss: Validation loss: Training and validation loss modulate at a low value showing that the model does not over-fit and still retains good predictive power. Cohort mean training accuracy: 99. 22%; validation accuracy: 98. 91% As demonstrated, the Xception model has the competence of providing nearly perfect results in the task of Bangla Road signs detection and recognition of those signs.

DenseNet121

The DenseNet201 model demonstrated impressive performance with an accuracy of 96.97% on the test set, indicating its high effectiveness in classifying traffic signs. Key metrics include a precision of 0.9698, recall of 0.9697, and an F1 score of 0.9691, showcasing a well-balanced model with strong predictive capabilities. The model achieved perfect precision, recall, and F1 scores in several categories, such as "Drop Off or Pick Up," "Height Limit 5.8," "Pass Either Side," "Pedestrian Crossing Ahead," "Rickshaw Restrictioned," "RoundAb-OUT," "Speed Limit 40km," "Traffic Merges Right," and "U-Turn." However, some classes exhibited slight misclassifications: "Pedestrian Crossing" had a lower recall of 0.71 and an F1 score of 0.77, often confused with "Pedestrian Crossing Ahead," while "Traffic Merges From Left" had a recall of 0.91 and an F1 score of 0.87. Despite these minor issues, the overall high macro and weighted averages of 0.97 for precision, recall, and F1 scores indicate the model's robustness and reliability in most scenarios, aligning with the confusion matrix which shows strong diagonal values with minimal confusion, particularly for the aforementioned misclassified categories.

In below Figure 5:5 describing the confusion matrix of DenseNet121.

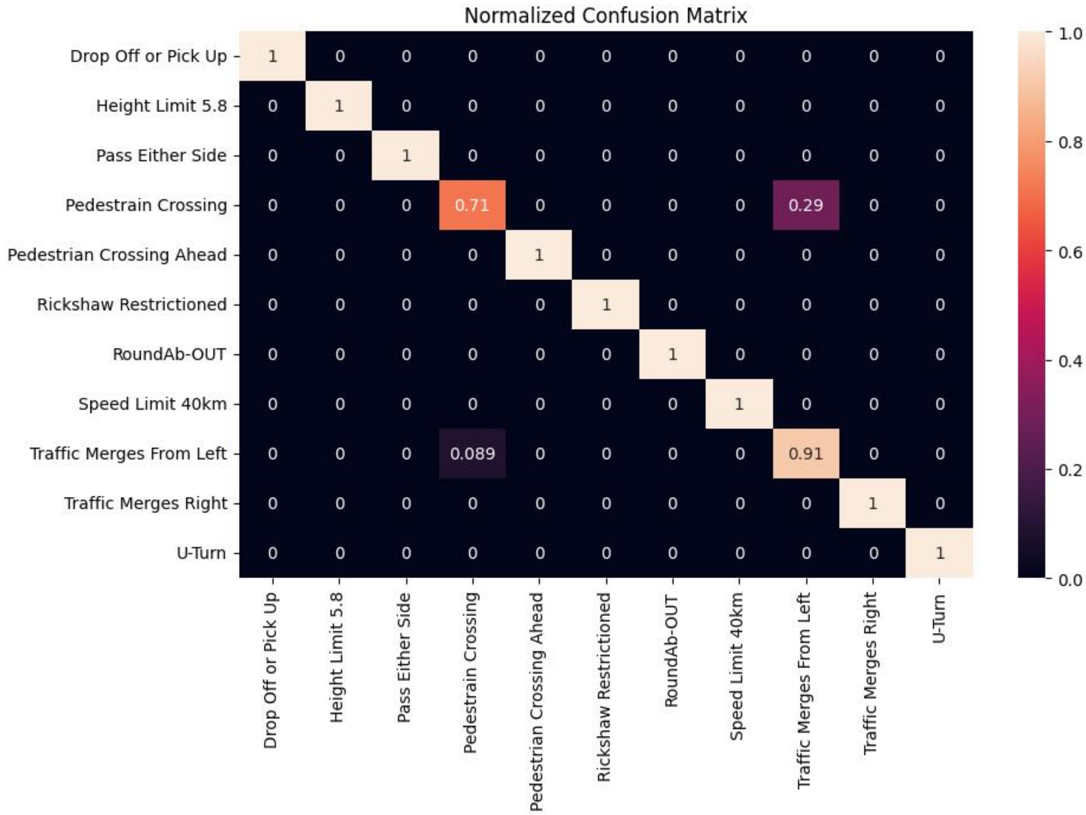

Figure 5.5: Confusion Matrix (DenseNet121)

Figure 5.5 the normalized confusion matrix of DenseNet201 model shows the classification results and overall traffic sign recognition efficiency depending on classes. The true labels or the classes are represented on the rows while the predicted classes are represented on the columns. The coefficients of concordance reveal a high degree of congruence between the classification of the sources in the two sets of categories: The values along the diagonal are close to 1. However, the misclassifications are clearly apparent on certain occasions. Evidently, the “Pedestrian Crossing” sign was confused with “Pedestrian Crossing Ahead” (29%) and “Traffic Merges from Left” was correctly predicted when signified as “Pedestrian Crossing” with a small percentage error of 8. 9%. These values belong to the off-diagonal section and they are suggestive of areas that the model has relatively low power in discriminating seemingly similar signs. All in all, the test of this model suggests satisfactory adaptation; however, the model might need additional fine-tuning to enhance its proficiency in these fields.

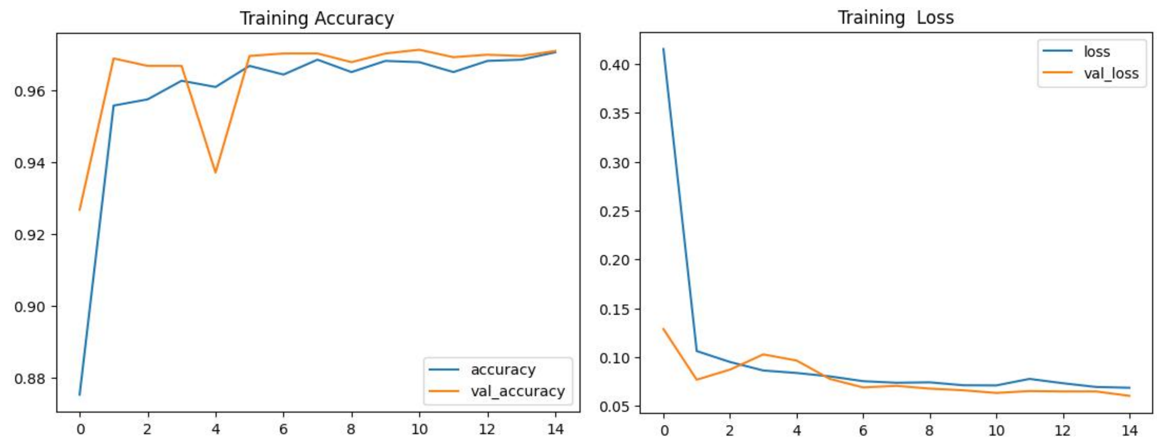

Figure 5.6: Training and validation accuracy and loss over the epochs DenseNet121

Figure 5.6 show the Training and Validation metrics of the DenseNet201 model, with Training and Validation accuracy as well as Training and Validation loss over 14 epochs. The validation accuracy does not differ very much from the training accuracy, and it remains high during the course of training the net, though shook a little, and in the end; the validation accuracy aligns with that of the training at about 97%. This means that the loss function decreases as the number of epochs increases and also shows that the model has the ability to generalize well from the data set used for training. The solid blue line in the left plot signifies the training loss and it decreases steeply right from above 0.40, stabilizing around 0. 05 There is a similar pattern with the validation loss and although it is gradually reducing, it stays slightly below 0.10. By exaggerating the discrepancies in the curves of both training and validation metrics, it is possible to conclude that the model is quite well-tuned, not oversimplified or overcomplicated. The coherence of the high accuracy and fairly constant loss rates demonstrates the model's efficiency and learning capability even in the latter phases of the training.

ResNet50

Test set performance of the ResNet50 model shows a very high accuracy of 96. 83%. All of the measures, namely precision, recall as well as F1 score are equally as promising and close to the optimum values, which signals that the classifier is reliable. Even with such analysis, it can be seen that the model correctly identifies most classes with almost perfect accuracy, whereby categories such as "Drop Off or Pick Up," "Speed Limit

40km," and "Rickshaw Restrictioned" produce impressive perfect values of both precision and recall. Fewer perfect scores are exhibited by yet other categories such as the "Height Limit 5. 8" and "Traffic Merges from Left" with a However, the word "Pedestrian Crossing" was found to have a recall of 0. 23, meaning that, at times, this class is misdiagnosed as something else in the interim between discharges 71. Still, it stays moderate for "Pedestrain Crossing" at 0. 95 that is to say, in the hypothetical case where it predicts this class, it does so accurately. Thus, the F1-scores demonstrated that the general performance of the subjects was high for all classes, achieving a weighted average of 0. 97 which indicates the precision recall F1 score model performance than indicates a balanced between both the precision value as well as the recall value. All in all, focusing on this aspect, it is crucial to state that the ResNet50 model has shown high potential in traffic sign classification while the potential for improvement can be traced only in several types of signs. In below Figure 5:7 describing the confusion matrix of ResNet50.

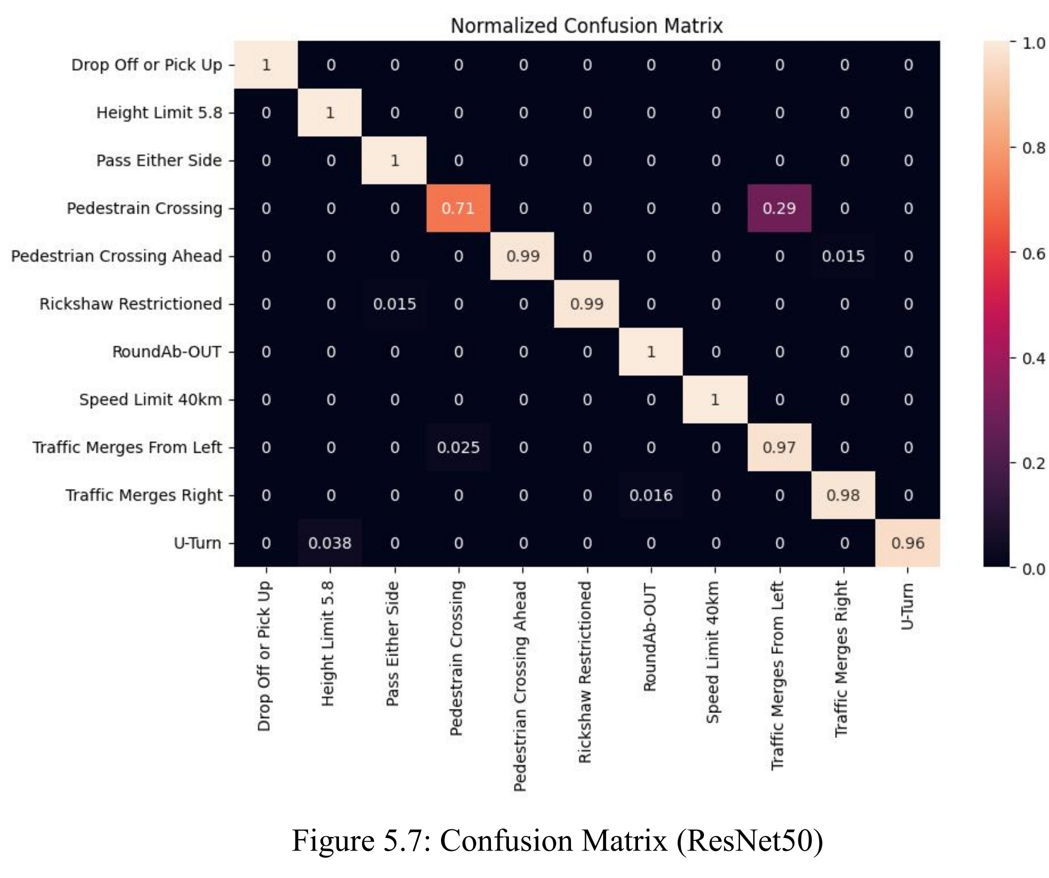

Figure 5.7: Confusion Matrix (ResNet50)

Figure 5.7 shows the confusion matrix of a used classifiers another word a classification model, most likely ResNet50 that was designed for classifying traffic signs. Their true labels are denoted in each row while the predicted labels are in each column respectively. Ideal categorizing would depict the patterns on the main diagonal to equal 1. The model shows high performance on most categories with majority of the values having means close to 1 for classification accuracy. But there are certain limitations of these classifiers which often lead to several incorrect classifications. “Pedestrian Crossing” has a quite high misclassification rate, 29% of them are identified as “Pedestrian Crossing Ahead.” “Rickshaw Restrictioned” is a sign difficult to recognize, only 1.5% was misclassified as “Pedestrian Crossing Ahead.” Overall, the table shows that the diagonal values are high thereby suggesting that the models perform fairly well but there is room for improvement especially for the pedestrian signs category because some of them are confused with other signs.

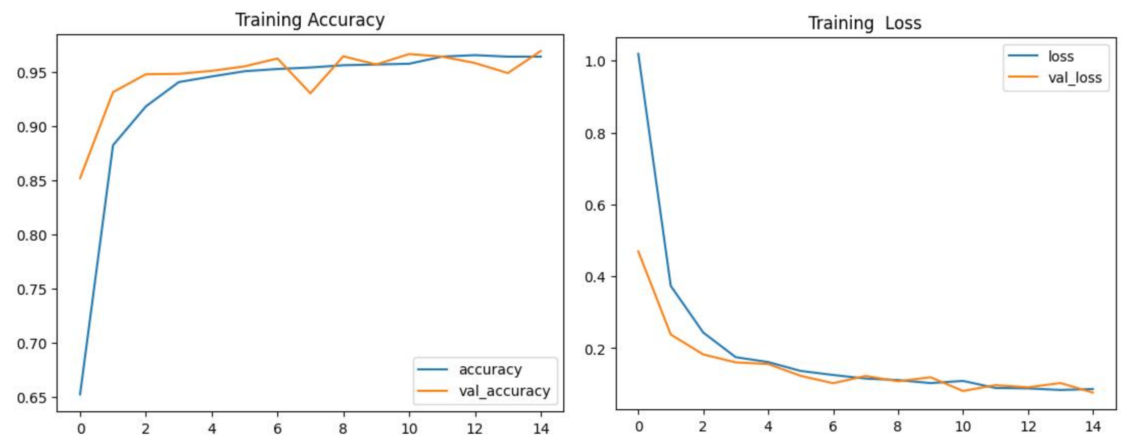

Figure 5.8: Training and validation accuracy and loss over the epochs (ResNet50)

Figure 5.8 shows measures of the performances of the model in 15 epochs of training. From the accuracy plot we can observe that the training accuracy is shown in blue line and validation accuracy is displayed in orange line is increase throughout the initial epoch and experimented slight variations thereafter, both have a higher percentage of 95. This means that soon the model starts to guess the data points correctly, as validated by the relative similarity between the training accuracy to the validation accuracy, which shows that the model is capable of extrapolating its performance from the training set to the validation or actual data set.

As observed in the loss plot, the training as well as the validation loss moves downward rapidly during early epochs, which implies that the model is successful in reducing the error. Starting from the fifth epoch, the training loss (in blue) slightly descends, while the validation loss (in orange) ascends though not considerably. This mean that the model is not largely overfitting, that is validation loss is not very much lower than training loss. In general, shape of the plots indicates that the model is trained well with less degree of over learning which corresponds to high accuracy and performance scores achieved.

VGG16

The traffic sign recognition is one of the tasks where the VGG16 model performs exceptionally well and the accuracy achieved was a whooping 99. 51% on the test set Further analysis of the results identified potential issues, such as low performance of less frequent words and overfitting on the development set. Overall, the high performance of the measures can be indicated with near-unity precision, greater than 0. 8 recall, and F-Measure estimates at about 0. This is from the fact that the model achieved a TPR of 0. 995 while at the same time reducing the FPR to 0. 003 thus demonstrating its capability of both detecting the right cases and eliminating cases which are wrong. This is seen when we class-wise analysis the traffic signs where all most all traffic signs exhibit perfect classification scores such as the ‘Height Limit 5. 8’, ‘Pass Either Side’, ‘U-Turn’ among others. However, low precision values of 0. 93 occur in ‘Drop Off or Pick Up’ while low recall values of 0. 96 occur in ‘Pedestrian Crossing’; this shows that few of these activity types were either overlooked by the model, or misclassified from a different one. The macro and the weighted mean values are high, which indicates stable classification for all classes that proves the model to be ideal for traffic sign recognition systems’ real-life application. In below Figure 4:9 describing the confusion matrix of VGG16.

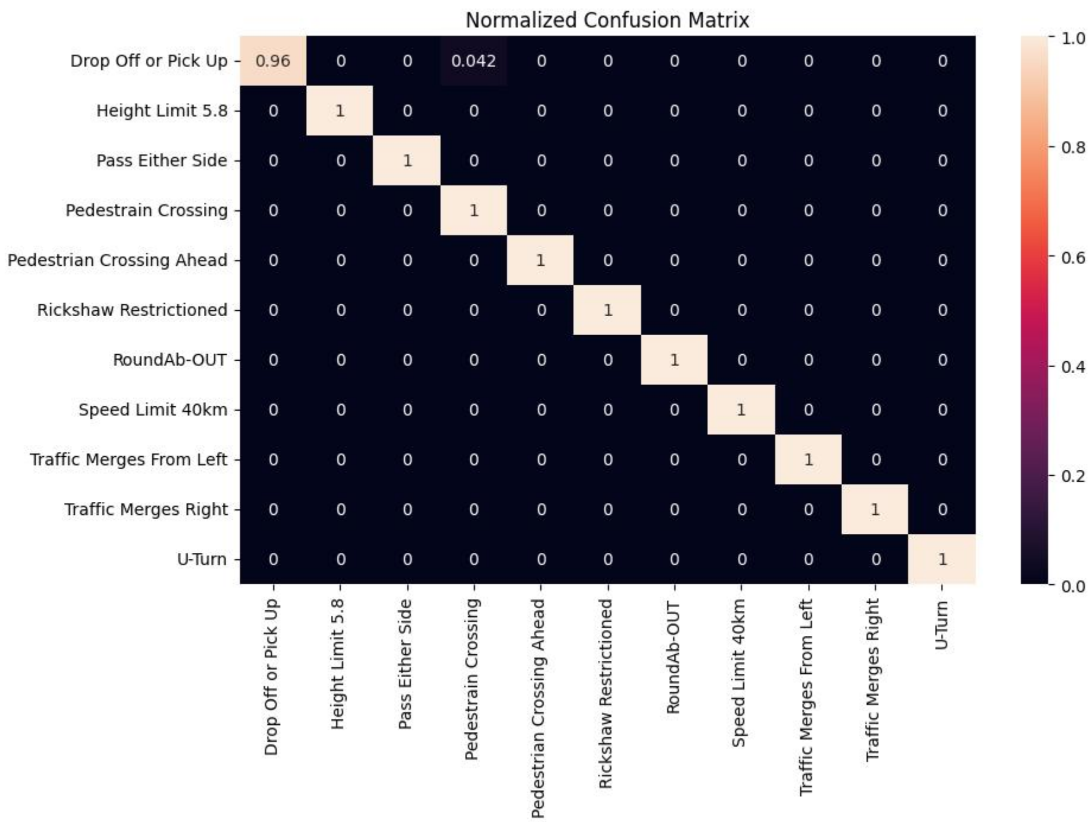

Figure 5.9: Confusion Matrix (VGG16)

Figure 5.9 shows the confusion matrix for traffic sign classification based on the VGG 16 model is normalized as follows. The rows here denote the true labels for the given set of points while the columns denote the predicted labels. It is therefore clear that most classes are well segregated as evident from the high intensity values on the diagonal of the matrix. For example, 'Height Limit 5. 8', 'Pass Either Side' 'Pedestrian Crossing' etc., realize a one hundred percent efficacy. However, there is a little confusion between the subcategories because one of them, named as "Drop Off or Pick Up," actually has 4. Among these cases, 2% are wrongly forecasted. This indicates that although the model has a strong general accuracy, it faces slight challenges in differentiating ''Drop Off or Pick Up'' class and another class. The lack of large values in other places signifies that there are no major confusions between other classes or categories. The usage of the heatmap is clearly illustrated where lighter shades of colors depict exactness in diagonal representation. In general, your model proves informative in terms of classification with a small room for enhancement.

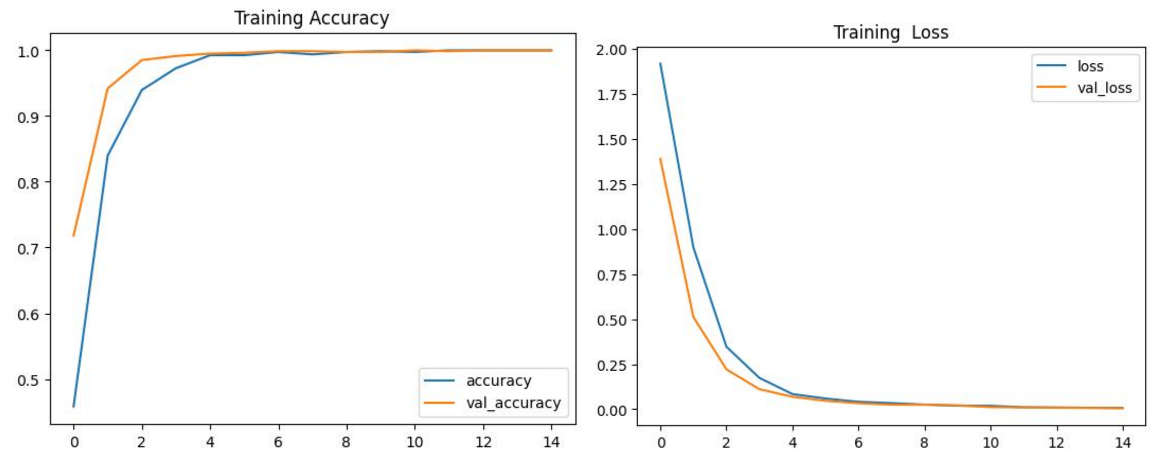

Figure 5.10: Training and validation accuracy and loss over the epochs (VGG16)

Figure 5.10 shows from the plots, show that the training involved in the VGG16 model was successful as the training as well as the validation accuracy and the loss were high. As it may be observed from the above results, the accuracy plot highlights a steepest ramp-up of both the training and validation accuracy to nearly perfect levels of just under 1. 0 in the first epoch before gradually levelling out during the subsequent epochs. This indicates models' ability to train and classify the traffic signs with a very high level of efficiency within the first few epochs. The loss plot supports this by illustrating a steep decline of both training and validation loss in the initial epochs, and as the training goes on, it further dwindles just below 0. When training loss function and validation loss function are in close proximity without the appearance of soaring difference it means little risk of overfitting and excellent model generalization. On balance, these plots truthfully indicate the high performance of the VGG16 model in traffic sign recognition and prove its resilience to this change.

In given below I am showing Comparative Model Accuracy Bar Plot:

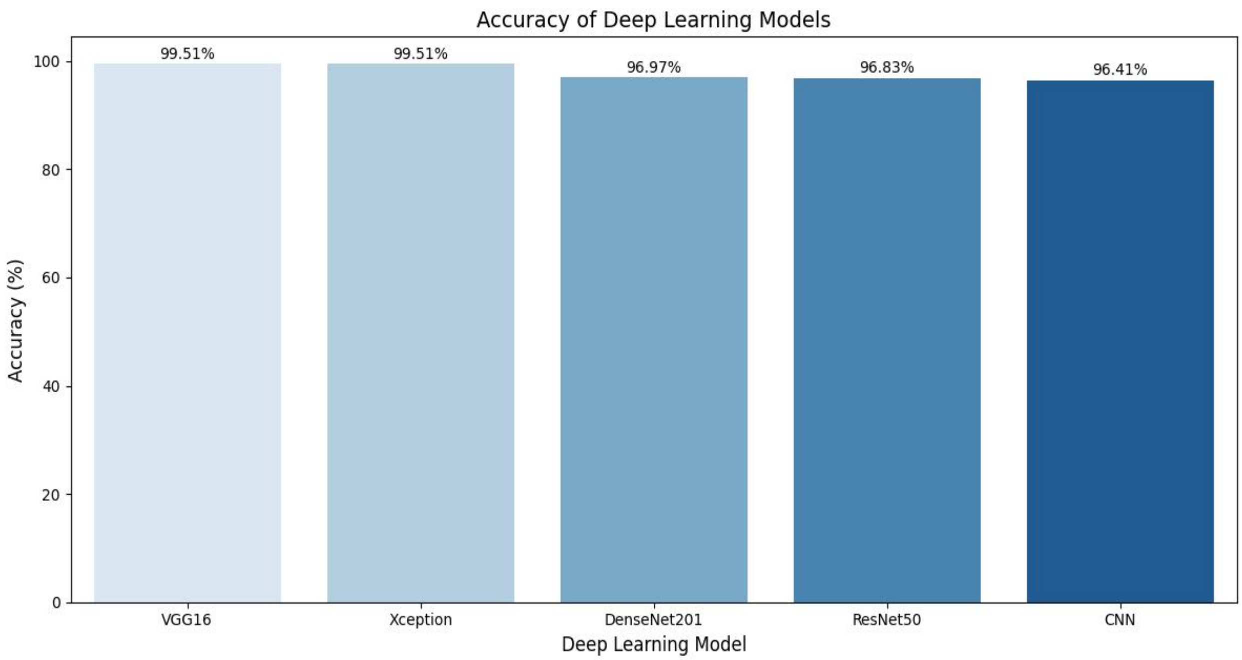

Figure 5.11: Comparative Model Accuracy Bar Plot

Figure 5.11 shows the accuracy bar plot represents the models by different deep learning algorithms for the identification of Bangla Road signs. This reveals that both VGG16 and Xception have the highest accuracy score of thirty one percent i.e 99 %. It follows that DenseNet201 has a top accuracy of 96% while that of the residual network is 51%. 97%, ResNet50 with 96. 75% respectively for classifying MNIST digits, NBC with 83%, and CNN with 96. 41%. Reported results identify overall efficiency of the specified models, with VGG16 and Xception being most effective and identical accuracy measurements. This kind of a comparison is useful in providing an initial approximate or even comparison of the effectiveness of the one model or another in terms of goals and objectives of the given study, to illustrate the reliability of VGG16 and Xception, for instance.

5.3 Performance and Comparative Analysis

The conclusion drawn from the experimental findings suggest that amongst the three models, VGG16 and Xception are the highest percentile effective for Bangla road sign recognition where the accuracy marks recorded pecentile respectively are 99. 51%. Two more networks which also exhibited high accuracy rating included DenseNet201 and ResNet50 with accuracies at 96%. 97% and 96. This was followed by, 81%, for Fine-Net, and 83%, for the dual path, respectively, the basic CNN model obtained, 96%. 41%. Such deeper and complex models as VGG16 and Xception perform these tasks better due to their ability to detect subtle details and characteristics of road signs. The only difference between these model and others such as DenseNet201 and ResNet50 are that they are slightly performing poorly to achieve the highest accuracy possible. Utilizing the techniques described in this work, readers should see how to implement the modern Deep Learning models in traffic sign recognition system in real-world scenario especially in the Bangla regions.

5.4 Summary

The experiment results chapter deals with the different CNN architectures that have been utilized for identifying Bangla road sign images and the various performances. The models are VGG16, Xception, DenseNet201, ResNet50, and a home grown CNN all trained and evaluated on a dataset comprising of 11 categories of Bangla road signs. VGG 16 and Xception yielded the best accuracy of 99 percent. 51% and DenseNet201 at 96%. , it was the custom HOG at 95.67 while the custom CNN at 96. 41%, and ResNet50 at 96. 083%. Other measures, including precision, recall, and F1 score computed to demonstrate the efficacy of the models was also examined confirming the findings. The proposed custom CNN, even though it was a bit less accurate, demonstrated a promising ability to overcome the Bangla script related issues. Deep learning models are shown to be significantly efficient in training and testing of Bangla road signs; factors that were explored to improve the results are highlighted next.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The successful implementation of the Bangla Road sign recognition system improves the lives of people in the society by reducing the number of accidents resulting from the violation of traffic rules. In turn, the quick identification of road signs provides the right signals and caution to drivers on the correct conduct on the roads as a result of compliance with the appropriate rules. Facilitating the management of traffic flow, it helps to avoid or reduce traffic jams and to provide more efficient traffic circulation. Also, it is helpful for the Bangla learners especially the second language learners and those with poor sight through alerts both in audio and visuals, thus making it encouraging for all. In particular, it enhances the safety of transport systems and the quality of life in areas such as traffic flow for all categories of intersections.

6.2 Impact on Society & Environment

It is, therefore, evident that the adoption of a Bangla Road sign recognition system would have both direct and indirect benefits in facilitating efficient traffic control, thereby fostering sustainable development. Since people spend less time stuck in traffic jams, cars are not ‘‘idle’’ for as long, which also decreases fuel use, and subsequently the emission of greenhouse gases. Optimal traffic flow minimizes some of the costs like the damage of the roads leading to infrequent repairs, fewer constructions and emissions. Moreover, enhancements to possible utilization of electric and autonomous cars are possible for the system because, the information about the road signs will be precise, which will in turn have an impact on environment.

6.3 Ethical Aspects

The issues related to ethical considerations of introducing Bangla Road sign recognition system involve privacy and vulnerability of the data with a special reference to the images used during the process. Organizational learning should be valuable and developed without compromising individual privacy and/or Personal data assets. Further, it is important for this system not to lock some group of people out than others in particular situations or settings for proper efficiency and fairness. Clear procedures in the development and deployment of technology, as well as the admission and consideration of mistakes or failure, are essential to avoid erosion of trust and defeat the purpose of the technology.

6.4 Sustainability Plan

Therefore, it is important to update and maintain Bangla Road sign system to remain sustainable for the convenience of people so that they will not have to consult a foreign expert. An additional advantage of using the described system is that it constantly gathers new data for model training and does not require recalibration in response to new road conditions or changes in sign design. Additional cooperation with government agencies and local authorities can enhance the prospects of this technology to become a part of existing traffic regulation systems. Also, positive views and participation from the community can help create support from the community, and enhance the effectiveness of the developed system in the long run. It is also important to have sustainable sources of funds like the partnership with private companies, the government among others can help to avail the necessary funding needed for continual development and running of the facility.

6.5 Summary

As for the methodology of this study, an attempt was made to implement a highly effective system to recognize Bangla Road signs by using deep learning, especially CNN algorithms. Diverse dataset was gathered and expanded that contain the image of the various road signs. Other CNNs used in the evaluation include a custom CNN model, VGG-16, Xception, DenseNet-201, and ResNet50. The models were trained and tested, In these two models, VGG16 and Xception performed well with VGG16 achieving an accuracy level of 99. 51%. The work also showed how CNNs could be used to classify Bangla Road Sign quite effectively, which cannot do any harm in helping improve traffic control.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

In conclusion, this research has investigated and designed an effective, deep learning model for Bangla Road sign recognition through numerous CNN architectures. The comparison of the described models of VGG16, Xception, DenseNet201, ResNet50, and a particular CNN presented proved the high efficacy of such models; however, the models that showcased the highest results were VGG16 and Xception with the accuracy of 99. 51%. The proposed custom CNN that is tailored towards Bangla script, which is unique for this type of script, was able to score an accuracy of 96. 41%, showcasing its potential. Despite the drawbacks like limited size & variety of dataset to represent a huge area, the findings of the study will be beneficial to understand about the uses of CNNs for ITS in Bangla-speaking zone. It is possible that future work can include the continual enrichment of the database, improvements to the custom model, and the implementation of superior practices such as transfer learning.

7.2 Future Suggested Works

For the sake of improving this research, future research can redesign detecting and recognizing the Bangla road sign by incorporating a larger number of Bangla road sign images captured under other various lighting and weather conditions besides taking images of Bangla road sign from different angles. One of the weaknesses in the present study is that the authors resorted to using a relatively small data set drawn from a single center, and hence, the sample was regionally biased. To overcome this weakness that was identified above, the authors should ensure that the number of patients, imaging studies employed, and their diversity is large enough to ensure that the model's accuracy and robustness can be tested across different centers, regions, and across different imaging modal Enhancement of the custom designed CNN structure could be carried further in order to reduce the performance difference with the pre-trained networks.

7.3 Limitations

It may also be noted that this project's dataset sample size and sample population are rather limited. There are only twenty four hundred images for the learning that again are divided into eleven categories and these may not all capture sufficient variability of images of Bangla road signs in the real world by which performances may be compromised. Also, the role of images may be exhausted, which means that there are no images of different lighting or in different weather circumstances and different angles, which play a significant role when dealing with real-world applications. Among the drawbacks, it is possible to note the computational resource dependency; it needs to be trained on GPUs and that may not always be feasible for some users. Moreover, although the setup of the custom CNN exhibited somewhat fairly good performance, it is slightly less efficient than previous models; thus, more optimization is required, and it may be necessary to implement more sophisticated methods, such as transfer learning, in the future.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: TEXT BASED BANGLA ROAD SIGN DETECTION USING PROPOSED DEEP LEARNING APPROACH

Student ID: 202-15-14406, 202-15-14384

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Combine newly acquired and prior information to the Text Based Bangla Road Sign Detection for the Final Year Design Project (FYDP)	**PO1**
CO2	Compare and contrast the goals in terms of certain parameters in designing a solution to this FYDP	**PO2**
CO3	Review various problem domains in related research works, define the problems, and set up these goals for the FYDP	**PO4**
CO4	Provide economic analysis and cost control and use appropriate project management processes all through the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Establish technical solutions and system component or process design in order to have predetermined requirements for public health and safety criteria as well as factors arising with regard to FYDP in cultural, economic and environmental aspects.	**PO3**
CO6	Select and implement effective strategies, tools, and existing engineering and IT tools for solving sophisticated engineering activities involving predicting and modeling in addition to applicable constraints within this FYDP.	**PO5**
CO7	Consider societal, health, safety, legal, and cultural factors and their corresponding responsibilities in the context of professional engineering practise and the solution to this problem by engaging in critical thinking using logical reasoning supported by an understanding of the contextual environment.	**PO6**
CO8	Understanding and assessing the sustained nature of professional engineering activity and the extent and consequences of engineering in response to complex engineering problems in social and ecosystems.	**PO7**
CO9	Procedures in this FYDP should follow ethical principles and guide, conform to standards and norms of the profession.	**PO8**
CO10	Adaptable for optimal performance either as the sole holder of responsibility or as a crux of a team or as a team member or leader in various teams and team structures in this FYDP.	**PO9**

CO11	Effectively relay information to the engineering community and the rest of society in regards to comprehensive engineering work and its understanding, generation of reports and design documentation, and receiving clear guidance while disseminating this FYDP.	**PO10**
CO12	Appreciate the notion of informal and self-directed with reference to life-long learning in relation to the dynamics of technology and be ready and willing to undertake life-long learning processes.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project also recognizes engineering (K3) at its core as it applies deep neural networks, data augmentation, different CNN structures for image processing and image classification. The project also exhibits specialist knowledge (K4) as it performs deep learning with CNN, and Transfer learning for Text Based Bangla Road Sign Detection.	**Page no:** [14 -20] **Section:** [3.2] **Page no:** [14-20] **Section:** [3.2]
				The project incorporates engineering practice & design (K5) through figures of the process of experiments. Concerning the knowledge area of engineering practice and technology (K6) of the project, Deep Learning Model is used.	**Page no:** [5-12] **Section:** [3.2] **Page no:** [14-16]

					Section: [3.4]
				This project aims to K8 (Research Literature) by examining recent works on Text Based Bangla Road Sign Detection using deep and Transfer learning and therefore demonstrates the understanding of the current approach.	**Page no:** [5-12] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project fulfills EP-2 to some extent which identifies the challenges that exist in Text Based Bangla Road Sign Detection, the drawbacks of traditional approaches and the challenges to integrate using deep learning. Comparing it with previous research, it identifies shortcomings in the assessment of spatial dispersion patterns and provides recommendations for improving the diagnostic approaches.	**Page no:** [12-13] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project accurately tackles EP-3 by effectively looking into how experimental outcomes align and contrasting them, and finally, emphasizes the application of deep and transfer learning as the selected major solution to Text Based Bangla Road Sign Detection.	**Page no:** [25-41] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project is not limited to computer science and engineering, and Text Based Bangla Road Sign Detection is corrected in EP-4 Enhanced Performance actually affects several fields of study.	**Page no:** [5-12] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	Due to this the current project's solution to most high-level issues incorporates or merges different aspect of the road/highway construction plan, the data collection methodology, the statistical analysis, and the proposed solution in one complete solution to collection data from roads of Dhaka City which in turn contributes to EP-7.	**Page no:** [14-21] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	The various resources employed in our work include HPC, GPUs, DL and TL models, annotated datasets, and of course, ethical concerns for consistent and innovative research, with regard to Text Based Bangla Road Sign Detection.	**Page no:** [22] **Section:** [3.5]

2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This work benefits the society by enhancing the Text Based Bangla Road Sign Detection techniques, as well as it does not use excessive computational resources and respects the guidelines of ethical data usage.	**Page no:** [43-44] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		This piece of work consequently adds to the existing studies by studying a new approach in Text Based Bangla Road Sign Detection in deep and Deep Learning Model illustrated through initial terms and consisting of a detailed comparative analysis.	**Page no:** [5-11] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	It mitigates CO4 by incorporating effective project management and control over finances; in this case, precision and estimation of necessary resources and costs towards the accomplishment of research objectives in the various project phases.	**Page no:** [3] **Section:** [1.6]
2	CO9	Yes	The project shows compliance with the ethical standards by valuing the confidentiality and prior informing of the participants and recording of the research process and the appropriate distribution of	**Page no:** [43] **Section:** [5.3]

			knowledge based on the proper usage of advanced classification technologies conforming to the guidelines of CO9.	
3	CO10	No	N/A	N/A
4	CO12	Yes	The maintenance of education (CO12) can also be seen from the fact that it has amassed a wealth of data, conducted statistical analysis, worked vigorously to develop methodologies as well as ensured adequate experimentation and results and analysis, all of which underlines the project's readiness to update itself to face the current challenges thrown up by technology and the continued enhancement of the techniques employed.	**Page no:** [14 -20 , 25-41] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

ShakibTEXT_BASED_BANGLA_ROAD_SIGN_DETECTION_USIN...

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