BANGLA DIGIT RECOGNITION ON AIR WRITING USING DEEP LEARNING TECHNIQUES

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CANDIDATE'S DECLARATION

It is hereby declared that the contents of this thesis are original and any part of it has not been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Bangla digit recognition on air writing has become a significant area of research due to its potential applications in human-computer interaction, digital learning, and assistive technologies. Many studies have been carried out in this area, leading to notable breakthroughs and great accuracy. Although the results were promising, there are still certain limitations to be addressed. These include lack of diversity in the datasets, misclassification of similar looking characters. To address these limitations, a dataset comprising approximately 5314 images from 200 participants, categorized into ten classes (0-9), was collected. Preprocessing steps, including resizing and data augmentation, were applied to enhance model robustness. Various deep learning models, including EfficientNetB0, InceptionV3, Inceptionresnetv2, Mobilenetv2, Resnet50, Resnet101, Vgg16, Vgg19 and Xception were utilized and fine-tuned for effective Bangla digit classification. Additionally early stopping and dropout (0.5) were employed during training as regularization the process and prevent overfitting. Furthermore models were evaluated on a validation dataset that contain 20% of the total images. Demonstrating high accuracy and strong performance metrics. It was found that VGG16 performed the best, with an accuracy of 98.91%, while MobileNet had the lowest accuracy, at 97.18%. Our findings contribute to the field of digit recognition on air writing and lay the groundwork for future research in air-writing recognition systems.

Keywords: Air writing, Bangla digit recognition, Gesture-based Bangla digit classification, Gesture recognition.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
Introduction

1.1 Overview

Bangla, or Bengali, used as an official language in Bangladesh and the second one in India, by the number of people who use it as their first language. Out of over 230 million speakers in the world, Bangla is counted among the most popular languages being used today [1]. Bangla digits are used in the Bangla numerals which is in use in the present day Bangladesh and some of the part of India [2]. Gesture recognition can be considered as a more distinct approach than the mere traditional ways of using knobs and buttons as it is based on detecting the users' intentions from their actions [3]. Bangla digits differ from symbols or numbers used in the English language. Writing in the air involves using gestures or trajectory information to write in 3D space, enabling a touchless system [4] allowing users to write in a touchless system [4]. The Bangla digits and their English counterparts are shown in the Table1.1.

Table 1.1: List of Bangla Digits and their corresponding English counterparts.

English Digits	**Bangla Digits**
0 (Zero)	০ (শূন্য)
1 (One)	১ (এক)
2 (Two)	২ (দুই)
3 (Three)	৩ (তিন)
4 (Four)	৪ (চার)
5 (Five)	৫ (পাঁচ)
6 (Six)	৬ (ছয়)
7 (Seven)	৭ (সাত)
8 (Eight)	৮ (আট)
9 (Nine)	৯ (নয়)

1.2 Problem Statement

The increasing number of applications requiring accurate and efficient digit recognition systems is driving the demand for digit recognition technology. These include, among other things, digital interfaces, security systems, and automated data entry. A shortage of Bangla digit datasets, however, poses an important challenge to this field and impedes the advancement of researchers and scientists who are developing Bangla digit recognition systems [2]. Another challenge in air-writing recognition is the non-uniformity of characters and the variability in writing styles, which complicates the consistent recognition of trajectories accurately [4]. There is an additional layer of complexity involved in accurately tracking small objects like the fingertip in images, especially when using webcams or standard laptop cameras. Identifying the writing hand pose, precisely identifying and tracking the fingertip, and identifying the air-writing character trajectory are the main challenges in this context [5]. Furthermore, air-writing requires continuous motion data with no discernible boundaries between writing and non-writing movements, so a strong system that can handle both detection and recognition tasks is required [6].

1.3 Motivation

Air-writing is fundamentally different from traditional handwriting because it doesn't involve writing on a surface and does not provide tactile feedback. This difference can lead to more variability and complexity in the motion data captured [3, 7] . Air writing technology enables touchless interaction, making it highly applicable in situations where traditional writing methods are challenging [4]. The motivation for this work is driven by the growing need for natural human-computer interaction systems due to the rise of virtual and augmented reality [8]. Also this technology carries the potential to assist individuals with speech challenges. Many individuals who struggle with speech are still capable of writing, and this application could be harnessed to track hand movements and convert them into synthesized human speech [3]. Writing with a fingertip in the air, using controller-free tracking systems, offers an innovative interface for text input when conventional devices are unavailable [6]. Traditional input methods are being

replaced by more intuitive methods. Developing a reliable air-writing recognition system addresses the limitations of existing hand gesture inputs, providing a more seamless and efficient way to interact with technology [8].

1.4 Objectives

Our thesis objectives are derived from the limitations of the existing thesis. These objectives are:

1. Create a diverse dataset of 5314 Bangla digit images contributed by 200 participants.

2. Train and Fine-tune different pre-trained models (EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18]) on the dataset.

3. Compare the performance of the aforementioned deep learning models on our newly build dataset to determine which is most effective for Bangla digit classification on air writing.

1.5 Social Impact

The development of air-written Bangla digit image classification systems has the potential to create significant social impacts. Primarily, it enhances accessibility for individuals with disabilities by enabling interaction with computers through simple hand gestures, serving as an alternative to traditional input devices [5, 6]. This technology can greatly improve the quality of life for people with motor impairments, providing reater independence in their digital interactions [12]. Additionally, air-written Bangla digit recognition can be integrated into educational tools to create interactive and engaging learning experiences. It helps young learners practice and learn Bangla numerals in a fun and intuitive way, promoting better retention and understanding [8]. In regions with limited access to advanced technology, this system offers an affordable and intuitive way to interact with digital devices, helping to bridge the digital divide and foster digital inclusion [9] Furthermore, the integration of air-writing recognition into

applications can lead to innovative human-computer interaction experiences, such as natural and immersive interactions in virtual reality (VR) and augmented reality (AR) environments. Implementing this technology also contributes to the preservation and promotion of the Bangla language in the digital age by facilitating its use in modern technology and supporting cultural heritage initiatives [4, 5].

1.6 Issues Encountered

These difficulties were resolved through research, expert consultation, and code customization. During the dataset collection phase, several challenges were encountered that affected the overall process. One significant issue was the difficulty in effectively communicating the instructions to the participants. Many participants struggled to understand how to write in the air in front of the camera, which led to inconsistencies in the collected images. Ensuring that each participant correctly performed the air writing task required additional time and effort. Another problem arose during the actual writing process. Participants often faced interruptions while writing, causing them to stop mid-way frequently. This disruption made it difficult to capture continuous and clear images of the air-written digits. Participants faced challenges in maintaining consistent writing, requiring repeated attempts to capture usable images. Clearer instructions and live demonstrations of the air writing process were provided to address this issue. However, further difficulties emerged, similar to those encountered in learning machine learning coding, such as significant delays and operational issues across different platforms.

1.7 Stakeholders

1. **Researcher:** Principal investigator responsible for the design, execution, and analysis of the study. Developed the script, processed the dataset, trained models, and compiled results into the thesis.

2. **Persons with Disabilities:** For people with disabilities, improved air writing recognition technology can facilitate communication and increase their access to digital content, fostering greater independence and inclusion.

3. **Education Sector:** Better methods for air writing Bangla numeral recognition and digitization can improve instructional materials and accessibility for pupils, including those with disabilities.

1.8 Summary

Explains the importance of Bangla as a major language and the particular difficulties in reading handwritten numbers in Bangla, particularly when using air writing techniques. It outlines the problem statement, highlighting the need for efficient and accurate Bangla digit recognition systems due to limited existing datasets and the growing demand for advanced HCI technologies. The chapter discusses the motivation behind using air-writing technology for Bangla digit recognition, emphasizing its potential to enhance human-computer interaction and its applications in education and assistive technologies. The objectives include creating a comprehensive dataset from 200 participants and evaluating various pre-trained models such as EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18] for classifying Bangla digit on air writings. It also addresses the social impact of this research, including improved accessibility, interactive learning, and cultural preservation. Challenges encountered during the dataset collection process, such as participant instructions and maintaining writing consistency, are also discussed. The chapter concludes with an overview of the thesis organization.

CHAPTER 2

Literature Review

2.1 Overview

Bangla digit recognition in air-written input utilizes deep learning and computer vision to interpret hand gestures in free space as characters, offering significant potential for accessibility and interactive applications. Accurate character and digit recognition in air-written input is greatly increased by using sophisticated models such as custom deep learning models like Long short-term memory (LSTM), Dynamic Time Warping (DTW) and Support Vector Machines (SVM) have been used, enhancing human-computer interaction and benefiting virtual reality, educational tools, and accessibility technologies [2, 4, 5].

2.2 Related Works

Numerous studies have been carried out in the field of air writing. For instance, Mahmud et al. [5] conducted a study on the recognition of English capital alphabets written in the air using depth information from a depth camera. The research involved capturing hand finger movements and representing them as depth images to extract trajectory data, which were then converted into time-series data. These data were classified using Dynamic Time Warping (DTW) distances and a multi-class Support Vector Machine (SVM), leveraging depth information to enhance the accuracy of air-writing gesture recognition. The methodology of the study included several key techniques. For data collection, two sets of datasets were prepared: one without depth information (390×260) and the other with depth information (390×312), along with their re-sampled versions. Additionally, three sets of datasets containing features related to correlation

analysis were prepared, resulting in a total of 12 datasets for evaluation. The dataset was split into k-folds for cross-validation (2-Fold, 5-Fold, 10-Fold, and 15-Fold) to train the model on all samples except the (k1) folds and evaluate it on the remaining fold, repeating this process k-times to record the average accuracy. Hand gestures were captured using a Microsoft Kinect depth camera, yielding a dataset of uppercase English letters at 640×480 pixels, 30 fps. Pre-processing included hand segmentation via depth information, extracting x, y coordinates for movement tracing, and applying a moving average filter for smoothing jerky motions. They used feature selection to avoid overfitting in machine learning, using Matlab and Weka with 155 DTW distance features. They checked accuracy using metrics like TPR, FPR, precision, recall, F-measure, ROC area, and PRC area, achieving 96.85% accuracy with Support Vector Machine classification. The study's limitations include a dataset created by only 15 users for air-writing recognition, possibly not reflecting broader handwriting or gesture styles. It focused solely on depth-based features and point vectors, neglecting other potentially informative feature types used in gesture recognition. Additionally, using only Support Vector Machine (SVM) without comparing it to other models or ensemble methods might have limited accuracy and robustness in classification tasks. However, the study urges further research with diverse datasets, more feature comparisons, and testing of different classifiers to enhance reliability and applicability of the findings.

In reference [2] Chayti Saha et al. conducted a study titled "Real-time Bangla Digit Recognition through Hand Gestures on Air Using Deep Learning and OpenCV". This research explores the real-time recognition of Bangla numerals through hand gestures, utilizing a Convolutional Neural Network (CNN) model for this purpose. The study addresses a significant gap in the field, as previous research on Bangla handwritten digit recognition had not successfully implemented real-time recognition using hand gestures. The methodology involves using the BanglaLekha-Isolated dataset, which contains a comprehensive set of handwritten Bangla characters. The authors preprocess the dataset through steps such as resizing, gray scaling, and augmentation. These preprocessed images are then fed into a CNN model designed to predict Bangla digits based on hand movements captured by a camera using OpenCV. The CNN was trained over 34 epochs, and the training and validation losses and accuracies were recorded.

The results demonstrate the system's effectiveness, achieving a 98.37% accuracy on the BanglaLekha-Isolated dataset. Additionally, without augmentation, the model reached a training accuracy of 99.36%, a validation accuracy of 97%, and a test accuracy of 97.30%. However, the study also highlights some limitations. Despite high training accuracy, the model struggled with recognizing enhanced real-time inputs, indicating potential overfitting. This suggests the need for further refinement in the model or improvements in data preprocessing techniques. Three primary limitations have been found: the size of the dataset used, which may constrain the model's generalization and performance on unseen data; variability in hand gestures, as differences in hand size, writing styles, and gestures among individuals could impact the model's accuracy; and limited computational resources, with the model implemented on an integrated computer with limited capabilities, potentially affecting its scalability and real-time performance on more resource-intensive platforms. The study successfully developed a real-time Bangla digit recognition system using hand gestures, setting a precedent for future research in this domain.

In study [4] Alam et al. present a trajectory-based air-writing recognition system using deep neural networks and depth sensors, focusing on recognizing characters written in free space. The methodology consists of four main parts: fingertip detection, data collection, normalization, and network design. Fingertip detection is performed using an Intel RealSense SR300 camera, which tracks the index fingertip for trajectory writing. Data is collected through an interactive UI from 10 participants aged 23 to 30, recording spatial trajectory sequences of written digits. Normalization techniques address challenges like shaky trajectories, with deep learning models (LSTM and CNN) eliminating the need for manual feature selection. The dataset comprises 21,000 digit trajectories, validated on both the self-collected RTD dataset and the 6D motion gesture (6DMG) dataset, achieving accuracies with LSTM of 99.17% and 99.32%, respectively, when normalized, and between 98.68% to 99.08% without normalization. The CNN model achieved 99.06% accuracy on both datasets with normalization, and between 98.26% to 98.89% without normalization. The LSTM model outperforms CNN, particularly with normalized data, showing superior performance across various conditions. The system's limitations include potential misclassification due to similar-looking characters

and reliance on RGB webcams without depth information, which can impact fingertip detection accuracy. Additionally, the system is primarily suited for gestures where the finger and palm lie in the same plane, with performance degrading when the fingertip points toward the camera. The study underscores the potential of deep learning in air-writing recognition, providing a practical and efficient solution while suggesting future work to enhance robustness, such as incorporating 3D hand pose estimation techniques. This innovative system offers significant contributions to the field, including a new dataset and improved recognition accuracy, highlighting the effectiveness of LSTM networks in trajectory-based air-writing recognition .

Research by Mukherjee et al. [8] studied the detection and tracking of fingertips for recognizing air-writing in videos. This study focuses on detecting and tracking fingertips for recognizing air-writing in videos. The authors address the challenge of accurate and robust detection and tracking of fingertips, which are often small and difficult to detect, using web-cam video inputs. The methodology involves several key steps: Hand Pose Detection utilizing the Faster R-CNN framework for precise hand detection, Hand Segmentation by segmenting the detected hand and counting the number of raised fingers based on geometrical properties, Fingertip Detection and Tracking employing a new signature function called distance-weighted curvature entropy, and Termination Criterion using a fingertip velocity-based termination criterion to mark the end of the air-writing gesture. The techniques used include Faster R-CNN for hand detection, geometrical analysis for finger counting, distance-weighted curvature entropy for fingertip detection and tracking, and a fingertip velocity-based criterion for gesture termination. The dataset consists of web-cam videos capturing mid-air finger writing, used to evaluate the proposed methodologies for hand pose detection, fingertip detection, and tracking. The results showed that the proposed fingertip detection and tracking algorithm achieved a mean precision of 73.1%, with real-time performance at 18.5 frames per second (fps). Character recognition experiments resulted in a mean accuracy of 96.11%, comparable to existing handwritten character recognition systems. Specific models achieved the following accuracies: Inception-v4 Accuracy: 98.12%, Inception-v3 Accuracy: 97.96%, ResNet Accuracy: 97.29%, VGG-16 Accuracy: 96.75%, and AlexNet Accuracy: 96.11%, with Inception-v4 achieving the highest accuracy and

AlexNet the lowest. The study acknowledges challenges in the initialization and termination of mid-air finger writing due to the absence of standard delimiting criteria, and although the precision of fingertip detection has improved, it still faces difficulties due to the small dimensions of the fingertip. This research provides a robust framework for detecting and tracking fingertips during air writing, improving precision and real-time performance. It holds great promise for practical applications in human-computer interaction. Table 2.2 has been created from the summary of the literature review.

Table 2.2: An overview of the reviewed literature.

Reference	**Dataset**	**Method**	**Result**	**Limitation**
Mukherjee et al [8].	Class: 36 Image: 11800	Faster R-CNN, DWCE	Precision: 73.1%, recognition: 96.11%, Incep-v4: 98.12%, Incep-v3: 97.96%, ResNet: 97.29%, VGG-16: 96.75%, AlexNet: 96.11%	Challenges in initialization and termination, Precision affected by small fingertip size
Alam et al [4].	Class:10 Total Images: 21000	LSTM, CNN	-LSTM normalization: 99.17%, without normalization: 98.68% - 99.08%, -CNN with normalization: 99.06%, without normalization: 98.26% - 98.89%	Misclassification of similar-looking characters, Accuracy impacted by RGB webcam limitations, Reduced performance when fingertip faces the camera
Chayti Saha et al [2].	Class: 10 Training image : 13,748 Testing image: 4000 validation image: 200	CNN model	Test Accuracy: 97.30%	Dataset size, Variability in hand gestures, Limited computational resources may affect generalization and real-time performance
Mahmud et al [5].	Class: 26 Total image :13950	SVM with DTW distance	Accuracy : 96.85%	Small dataset , Limited to depth-based features

2.3 Summary

Explores a detailed review of pertinent literature, emphasizing studies investigating Bangla digit recognition through air writing methodologies. The chapter methodically reviews the methodologies used in these investigations, emphasizing their strengths and shortcomings. This study provides a strong foundation for understanding the current state of research in the field of Bangla digit recognition on air writing. Key themes and findings from the literature highlight the gaps that this thesis aims to address, setting the stage for the following chapters.

CHAPTER 3

Methodology

3.1 Overview

Describes the steps involved in air writing Bangla digit recognition, including data collection, preprocessing, model development, and evaluation. Using cameras, Bangla digit air writing images were taken for data collection. A dataset containing thorough descriptions of sample numbers and participant demographics was then assembled. Normalization for image standardization and augmentation for dataset diversity were two examples of data preprocessing. The process of developing a model involved choosing an algorithm, training with preprocessed data, and assessing performance with metrics. The validity and reliability of the study's conclusions are guaranteed by this methodical approach.

3.2 Data Collection and Preprocessing

Regarding Bangla digit recognition using air writing techniques , a comprehensive dataset was collected, consisting of 5,314 images categorized into 10 classes representing the Bangla digits from 0 to 9. The air writing gestures were performed in controlled environments and captured using advanced sensors and high-resolution cameras to ensure high-quality data. The dataset includes diverse writing styles and variations, providing a robust foundation for training and evaluating the classification model. This extensive collection of images contributes significantly to the reliability and validity of the study's findings. The gathered dataset was carefully preprocessed in order to remove noise and standardize the images. Comprehensive data augmentation methods were also used to improve the model's resilience and capacity for generalization.

3.2.1 Data Sources

The dataset was gathered from 200 participants selected from BAUST, ensuring a diverse range of writing styles and variations. Among these participants, 70 were female and 130 were male, coming from various backgrounds. The air writing gestures were performed in controlled environments and captured using advanced sensors and high-resolution camera (Logitech C270 720p Hd Webcam) to ensure high-quality data. This robust dataset, consisting of 5,314 images categorized into 10 classes representing the Bangla digits from 0 to 9, provides a solid foundation for training and evaluating the classification model, contributing significantly to the reliability and validity of the study's findings.

3.2.2 Data Collection Techniques

1. **Participant Recruitments:** Gather a diverse group of approximately 200 participants to ensure variability in handwriting styles. Participants were recruited from BAUST. Recruitment ensured a mix of different genders and backgrounds for comprehensive data collection. Among the 200 participants, 70 were women, and the remaining were men.

2. **Setting Up the Environment :**

   (a) **Hardware Requirements:** Data collection for the Bangla digit image classification thesis was conducted through air writing using a customized Python [19] script called "Airwriting.py". The script recorded air writing movements using the built-in cameras of two different laptops, HP laptop and an ASUS TUF F15. The laptop's camera was set to record video input automatically when the "Airwriting.py" script ran.

   (b) **Software Requirements:** The "Airwriting.py" script was used to capture images of airwritten Bangla digits. This script was developed in a Python [19] environment with several necessary libraries installed, including OpenCV [20] for real-time computer vision tasks, NumPy [19] for numerical operations, and other standard libraries required for video processing and image manipulation. The combination of these software tools ensured the accu-

rate detection and capture of digits written on air during the data collection process.

3. **Data Collection:** Ensure that all required components are initialized before starting to record and analyze numbers written in the air. . This involves loading essential libraries like OpenCV [20] and NumPy [19], crucial for image processing and data manipulation tasks. Additionally, set up the camera to seamlessly capture video feeds, ensuring clarity and consistency in the digit recognition process. Once initialized, the capturing process can commence effectively. Participants are prompted to airwrite each digit (0-9) multiple times in front of the camera. This process involves executing the "Airwriting.py" script within the Python environment, where participants enter their ID to begin. They follow on-screen instructions to position their hand correctly and execute the airwriting motion. Frames are captured when the digit is clearly visible, with options to save each frame by pressing 's' or quit the process with 'q'. Each captured frame is then extracted and saved as an individual image, properly labeled for future analysis or machine learning model training. This structured approach ensures a comprehensive dataset for accurate digit recognition research or application development.

4. **Organizing the Data:** Organize air-written digit images by first creating a folder for each person. Inside each person's folder, make separate folders for digits 0 through 9. When capturing images, save them directly into the correct digit folders. Name each image using the format "digit-label-image_number," ensuring each file is named with the digit written, its label (like "0" for the digit '0'), and a number to sequence them. This method ensures clarity and easy sorting of the images for future reference or analysis.

3.3 Preprocessing Steps

Data preprocessing is a crucial step in preparing the raw collected dataset for training a machine learning model. Images were preprocessed using Keras [21] ImageDataGenerator [22]. Figure 3.1 illustrates a process for preparing raw images for inclusion in a dataset. For training, augmentations included rescaling, random shear, zoom, brightness and contrast adjustment, noise injection, random cropping, and elastic distortion

to increase dataset diversity. Validation data was only rescaled for normalization. Both datasets were resized to 224x224 pixels to ensure uniform input size for the neural network.

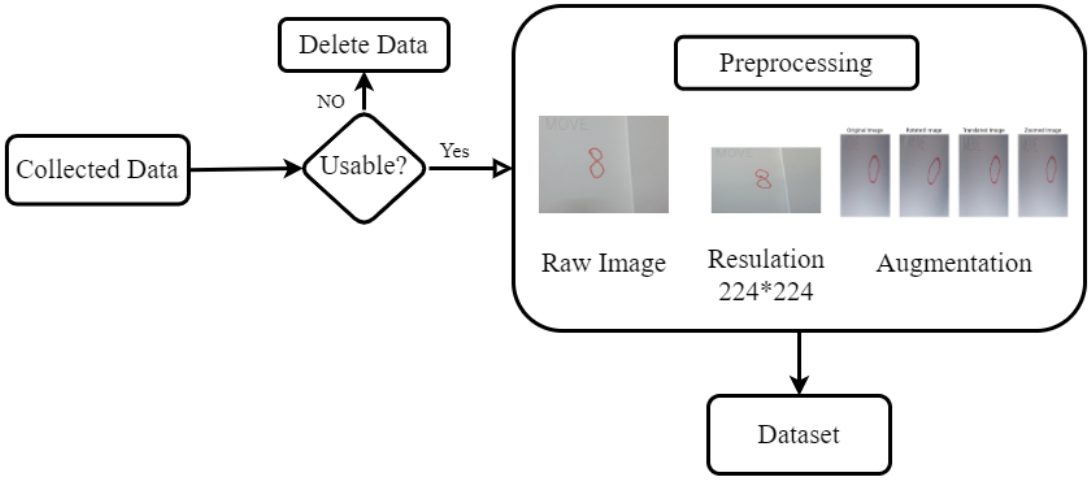


Figure 3.1: Data preprocessing steps.

3.3.1 Data Preprocessing Procedure

1. **Import Necessary Libraries:** Import essential libraries such as TensorFlow [23], Keras [21], NumPy [19], and OpenCV [20] for handling image data and model training.

2. **Load and Inspect Data:** Load the collected dataset from its directory.Inspect a few samples to understand the structure and quality of the data.

Figure 3.2: Loaded data.

3. **Image Resizing:** Resize all images to a uniform size of 224x224 pixels. This ensures that the input dimensions are consistent, which is crucial for feeding the images into the neural network.

4. **Data Augmentation:** To enhance training data diversity and improve model generalization, use Keras' ImageDataGenerator to perform real-time data augmentation with techniques such as random rotations, shifts, flips, and zooms. This generator creates batches of augmented tensor image data on-the-fly during training, thereby increasing dataset variability without additional data collection.

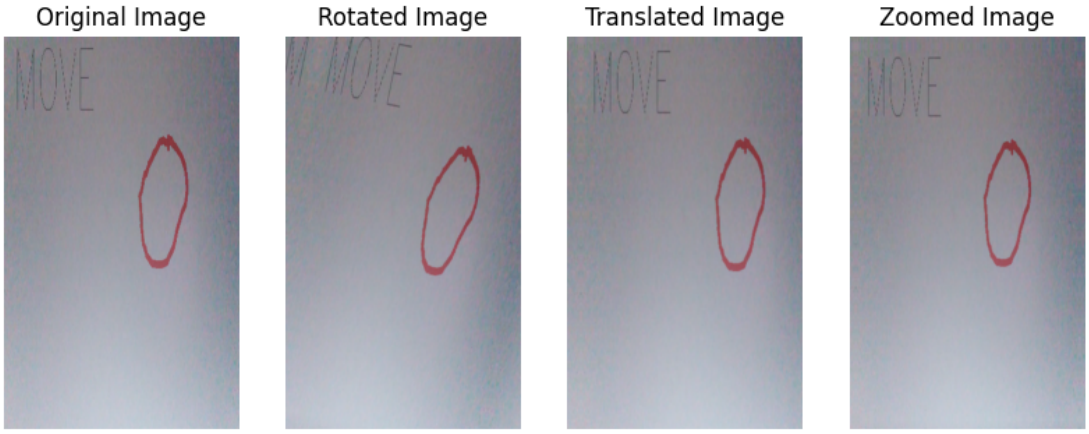


Figure 3.3: Augmented data.

Random Rotation: Calculate the rotation matrix:

$$\text{Rotation Matrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$

For each pixel in the original image, apply the rotation matrix to calculate the new coordinates:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \text{Rotation Matrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix}$$

Random Zooming: For each pixel in the original image, scale the coordinates by the random zoom factor:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \alpha \begin{bmatrix} x \\ y \end{bmatrix}$$

Random Contrast Adjustment: For each pixel intensity value I in the original image, adjust the intensity using the random contrast adjustment factor β:

$$I' = \beta \cdot I + I$$

Split Dataset: Split the dataset into training, validation, and test sets. Typically, the dataset is split into 80% for training, for validation & testing 20%. This helps in evaluating the model's performance and fine-tuning it effectively.

3.4 Pre-trained Models

3.4.1 Xception

Xception[18] is a highly accurate and computationally efficient convolutional neural network, ideal for real-time applications. It employs depthwise separable convolutions, reducing parameters and computations. Residual connections in Xception prevent vanishing gradients, enhancing training stability and effectiveness. The architecture balances high performance with reduced computational cost. Figure 3.4 shows the Xception architecture.

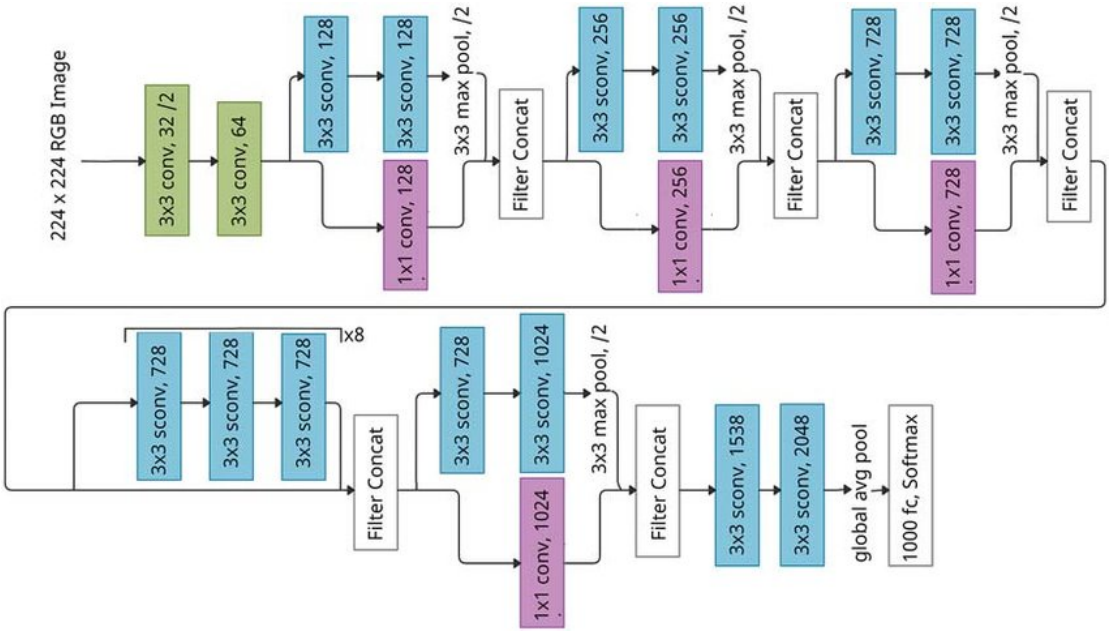


Figure 3.4: The Xception architecture.

3.4.2 InceptionV3

InceptionV3 [10] is a convolutional neural network architecture renowned for its strong performance in image classification, largely due to its inception modules. These modules incorporate convolutional filters of varying sizes within a single layer, enabling the network to effectively capture features at multiple scales. The architecture of InceptionV3 includes layers of stacked inception modules, each featuring simultaneous 1x1, 3x3, and 5x5 convolutional filters, as well as a pooling layer. This arrangement allows the network to learn a variety of features concurrently, enhancing its ability to quickly extract and interpret complex visual data. Figure 3.5 shows InceptionV3 architecture.

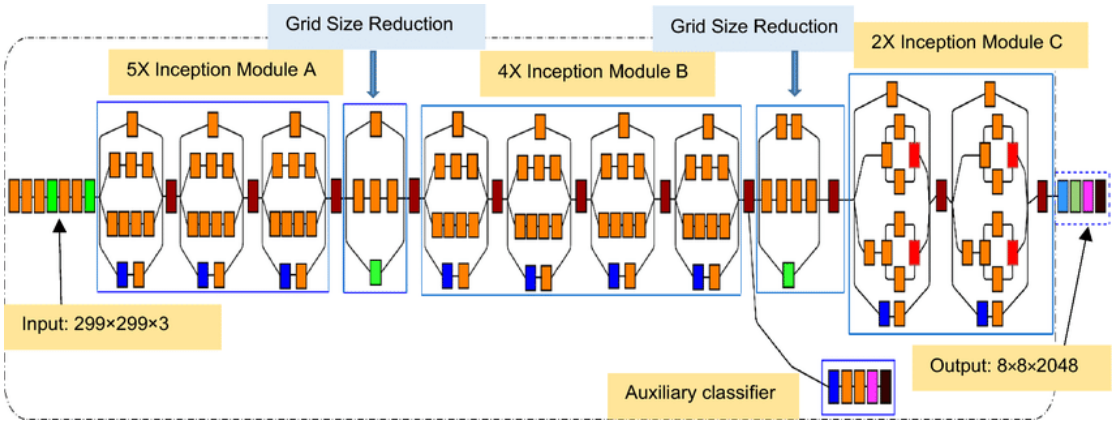


Figure 3.5: The Inception-V3 architecture.

3.4.3 Inceptionresnetv2

InceptionResNetV2 [11] is a deep convolutional neural network that combines the strengths of Inception architectures and residual connections. Introduced by Szegedy et al. in 2016, it leverages the advantages of both Inception modules, which are adept at handling various spatial dimensions, and residual connections that help in training very deep networks. The model features repeated Inception blocks interspersed with residual connections, allowing for efficient training and improved accuracy. It is widely used in image recognition tasks due to its robust performance and relatively lower computational cost compared to other deep architectures. The InceptionResNetV2 architecture is designed to handle complex image classification tasks with a high degree of efficiency. Its use of Inception modules allows the network to capture fine-grained details at multiple scales, making it adept at recognizing intricate patterns in images. The inte-

gration of residual connections helps to mitigate the vanishing gradient problem, which is common in very deep networks, ensuring that the gradient flow is preserved during backpropagation. This combination of techniques enables InceptionResNetV2 to achieve state-of-the-art performance on various benchmark datasets. Figure 3.6 shows Xception architecture.

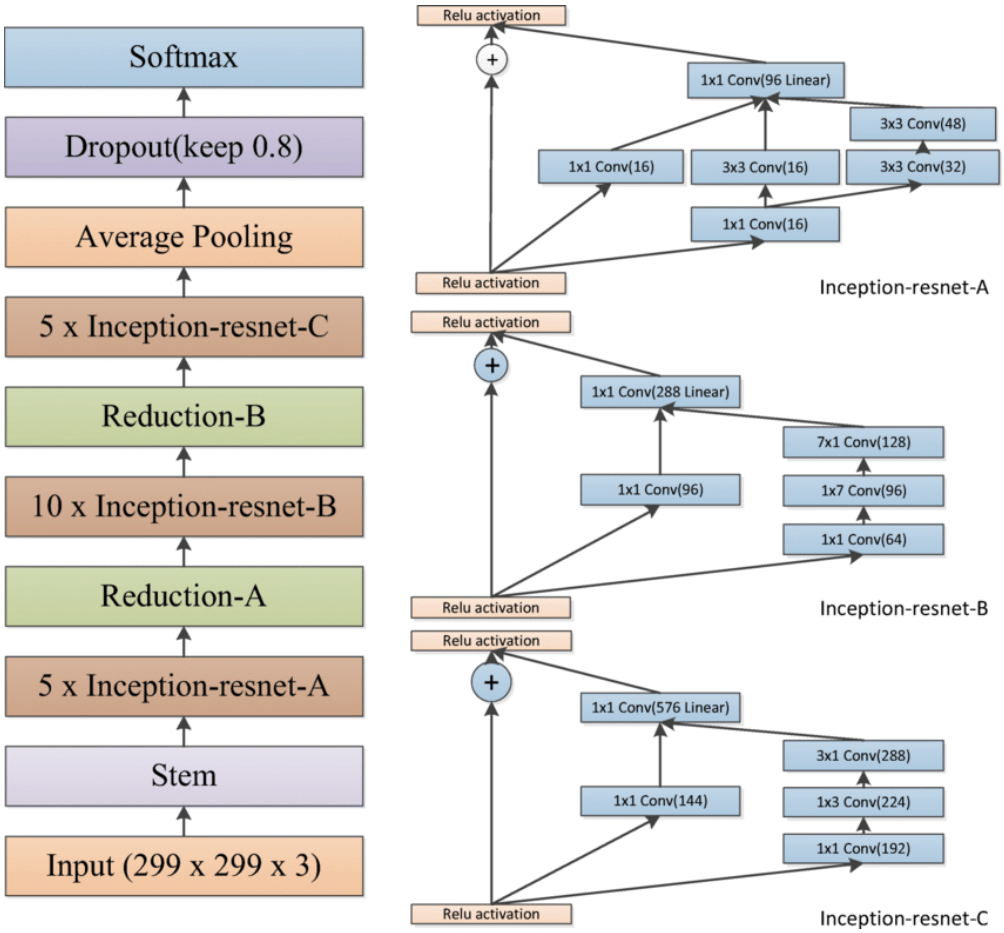


Figure 3.6: The Inceptionresnetv2 architecture.

3.4.4 MobileNet

MobileNet [12] is a family of lightweight deep neural network architectures designed by Google for efficient performance on mobile and embedded devices. Introduced in 2017, it employs depthwise separable convolutions, significantly reducing the number of parameters and computational cost compared to traditional convolutional networks. MobileNet models are scalable, allowing adjustments in the width and resolution of the network to balance accuracy and efficiency. They are widely used in various applications, including image classification, object detection, and mobile vision tasks, due to

their high performance and low resource requirements. MobileNet's architecture also supports the use of neural network accelerators, further enhancing its suitability for edge computing scenarios. Its flexibility makes it ideal for deploying deep learning models on resource-limited devices. Figure **??** shows MobileNet architecture. Additionally, MobileNet's modular design facilitates easy integration with various machine learning frameworks, providing developers with the tools to optimize their models for specific use cases. Recent advancements have further improved its capabilities, ensuring its relevance in the rapidly evolving field of mobile AI. With continuous updates and a strong community support, MobileNet remains a popular choice for on-device machine learning solutions.

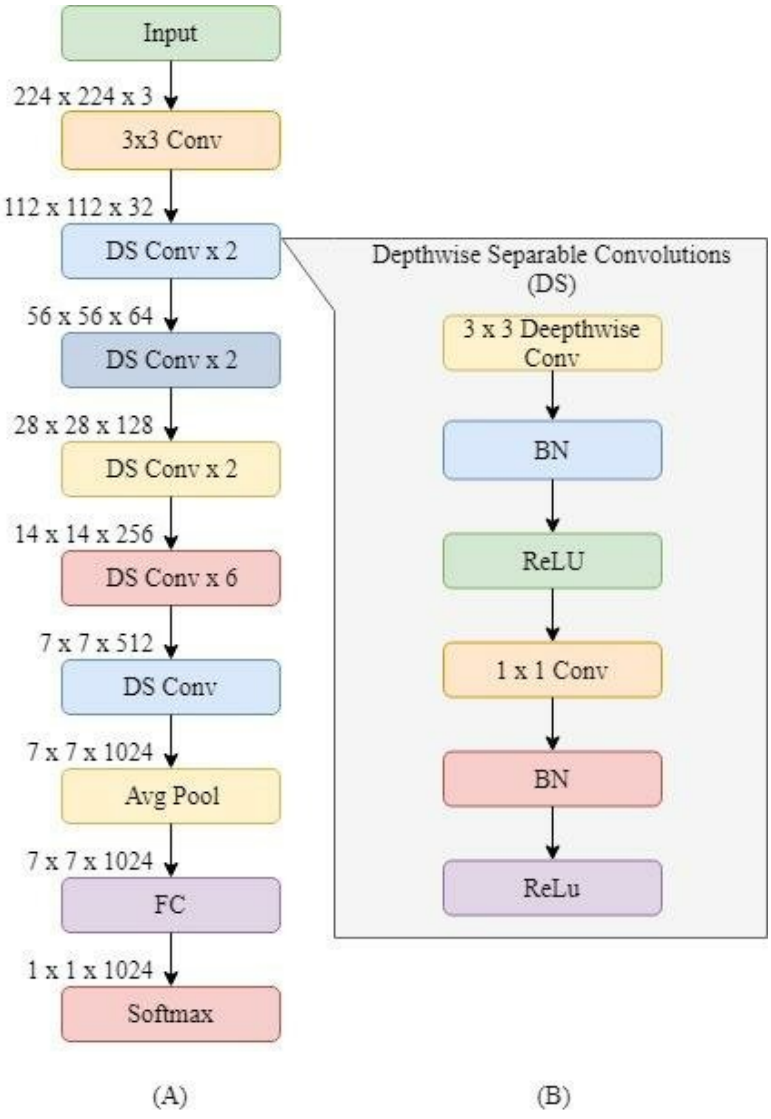


Figure 3.7: The MobileNet architecture.

3.4.5 MobileNetV2

MobileNetV2 [13] is a convolutional neural network architecture optimized for mobile and embedded vision applications. It introduces inverted residuals with linear bottlenecks, where intermediate expansion layers have more channels than the input and output layers, preserving information while reducing dimensions efficiently. The architecture uses depthwise separable convolutions to minimize parameters and computations, splitting the convolution operation into independent filtering and combining steps. Additionally, MobileNetV2 eliminates non-linearities in narrow layers to retain important features. These innovations make MobileNetV2 highly efficient, achieving a balance between model size, speed, and accuracy, ideal for mobile and edge device applications. Figure 3.8 shows MobileNetV2 architecture.

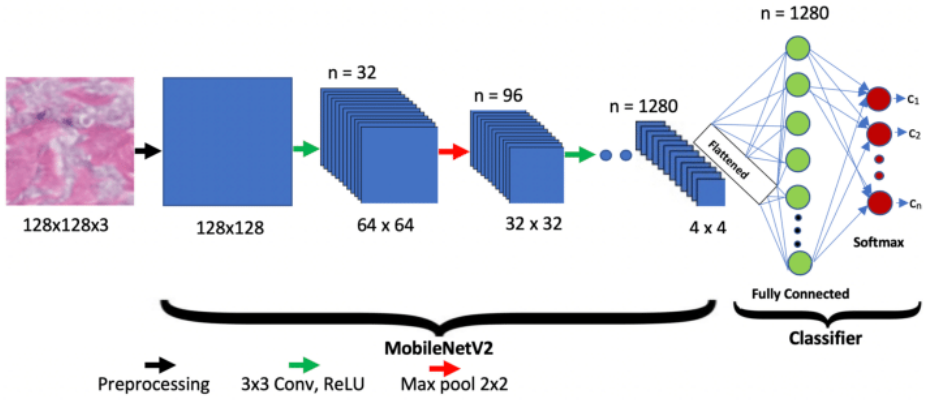


Figure 3.8: The MobileNetV2 architecture.

3.4.6 EfficientNetB0

EfficientNetB0 [9] is a convolutional neural network architecture designed for high performance and efficiency in image classification tasks. It is the baseline model in the EfficientNet family, which scales up the network's width, depth, and resolution in a balanced manner using a compound scaling method. This approach enables EfficientNetB0 to achieve superior accuracy while using fewer parameters and computational resources compared to previous architectures. EfficientNetB0 utilizes mobile inverted bottleneck convolution (MBConv) layers with squeeze-and-excitation optimization, enhancing feature extraction and reducing model size. This makes EfficientNetB0 ideal

for deployment in resource-constrained environments, providing a good balance between accuracy and efficiency. Figure 3.9 shows EfficientNetB0 architecture.

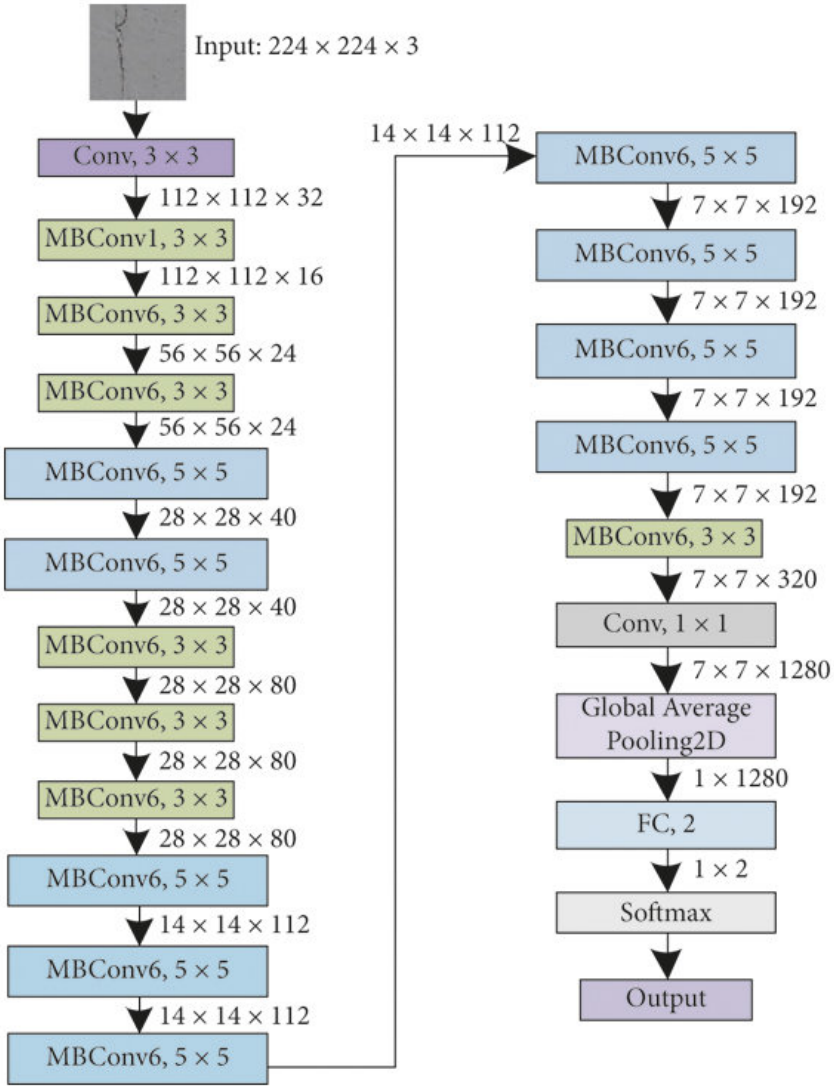


Figure 3.9: The EfficientNetB0 architecture.

3.4.7 Resnet50

ResNet50's [14] design, featuring residual connections, addresses the vanishing gradient problem in deep networks, enabling efficient training of its 50 layers. This balance of depth and efficiency makes it a preferred choice for diverse computer vision tasks, from segmentation to image classification.recognition tasks. Introduced by He et al. in 2015, it utilizes residual connections to allow the training of very deep networks by addressing the vanishing gradient problem. These skip connections help in learning

residual functions with reference to the layer inputs, making it easier to optimize deeper networks. Figure 3.10 shows Xception architecture.

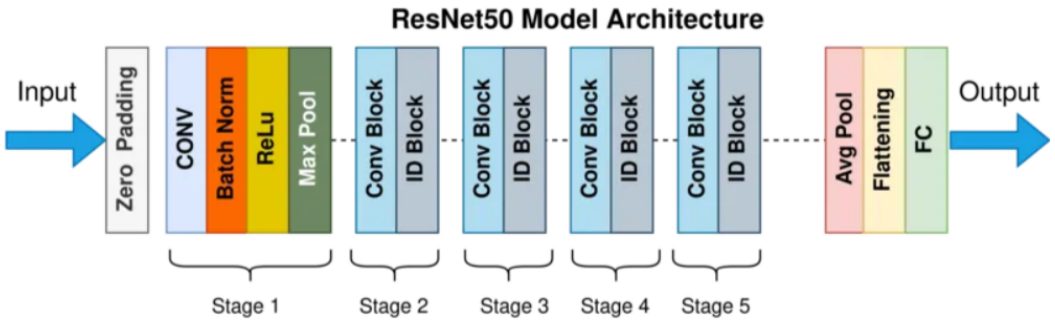


Figure 3.10: The Resnet50 architecture.

3.4.8 Resnet101

ResNet101 [15] is a deep convolutional neural network that extends the ResNet (Residual Network) architecture to 101 layers. Figure 3.11 shows Resnet101 architecture. ResNet101 is renowned for its strong performance in image classification, object detection, and segmentation tasks, offering higher accuracy compared to its shallower counterparts like ResNet50, while maintaining a manageable computational load.

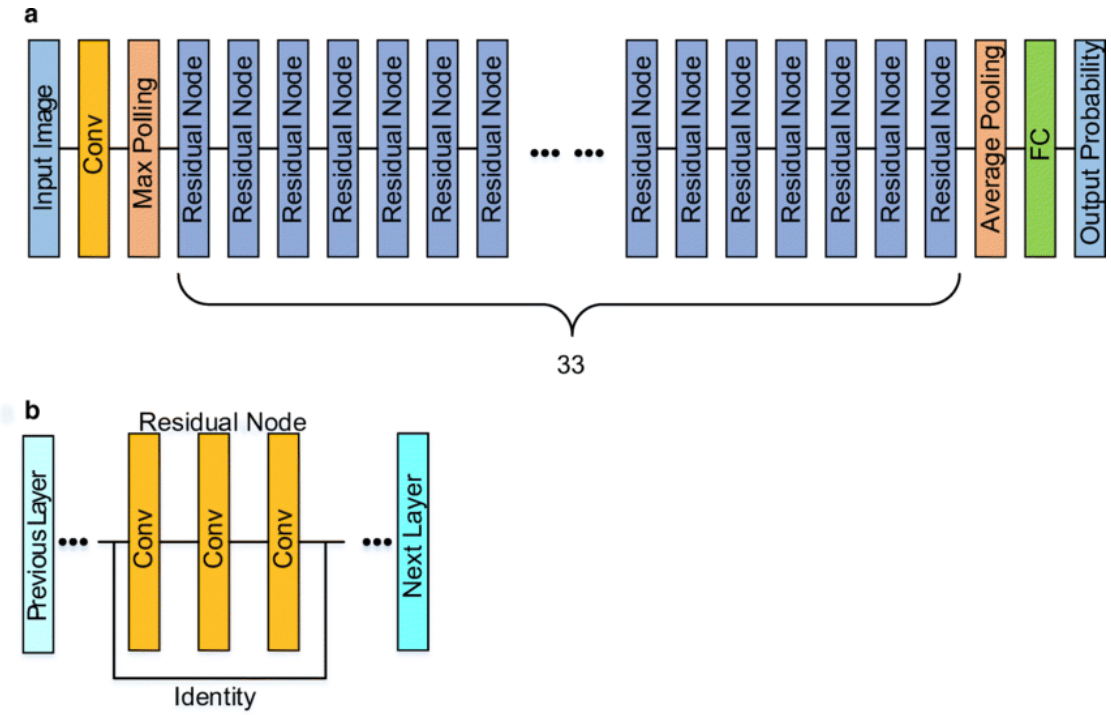


Figure 3.11: The Resnet101 architecture.

3.4.9 Vgg16

The University of Oxford's Visual Geometry Group (VGG) unveiled the convolutional neural network architecture known as VGG16 [16] in 2014.There are three fully connected layers and thirteen convolutional layers among its sixteen weight layers. Utilizing tiny 3x3 convolution filters that are stacked to increase the network's depth, the design places an emphasis on simplicity. The VGG16 architecture is renowned for consistent and for performing exceptionally well in image classification tasks. Because of its great accuracy and simplicity of use, is still widely used even though it requires a amount of memory and is computationally demanding. It is frequently utilized as a standard in many different computer applications. Figure 3.12 shows Vgg16 architecture.

Figure 3.12: The Vgg16 architecture.

3.4.10 Vgg19

VGG19 [17] is a deep convolutional neural network architecture developed by the Visual Geometry Group (VGG) at the University of Oxford, introduced in 2014. It is an extension of the VGG16 model, featuring 19 weight layers—16 convolutional layers and 3 fully connected layers. The network uses small 3x3 convolution filters throughout its architecture, stacked to create deep networks capable of capturing intricate features. VGG19 is known for its simplicity and effectiveness in image classification tasks, achieving high accuracy. Despite its high computational cost and memory requirements, it remains widely used for its performance and has become a standard benchmark in computer vision research. The model's architecture is characterized by its uniform design, using the same convolution filter size and max-pooling layers after each set of convolutional layers. This consistency allows for easier implementation and

fine-tuning. VGG19 has been successfully applied in various domains beyond image classification, including object detection and image segmentation. Figure 3.13 shows Xception architecture.

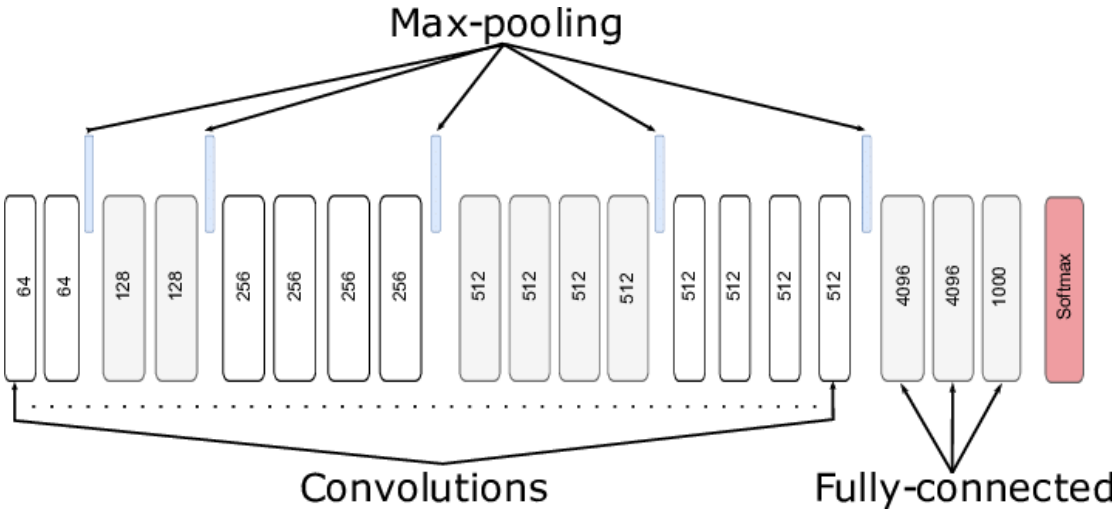


Figure 3.13: The VGG19 architecture.

3.5 Flow Diagram of Methodology

The methodology outlined in the flowchart is designed to classify handwritten digits through air writing, which is particularly relevant to your thesis topic on Bangla digit image classification. The process starts with a video stream that captures the hand movements of users. This video stream serves as the primary input for the system. The first major step in the process is hand pose detection. The system continuously monitors the video stream for the presence of a hand pose. If no hand pose is detected, the system keeps checking the video stream. However, once a hand pose is detected, the system moves to the next step, which is fingertip detection. During fingertip detection, the system assesses whether the detected fingertip velocity is below threshold (t). This is crucial because it helps in distinguishing intentional writing gestures from random hand movements. If the fingertip velocity is above the threshold, indicating rapid or non-writing movements, the system may disregard this data. But if the velocity is below the threshold, the system assumes the hand is in a writing motion and proceeds to record the digit trajectory. The digit trajectory is then outputted, forming a raw representation of the written digit. To ensure the system is trained on a diverse dataset, data is collected from 200 different individuals. This dataset helps in making the model

robust and generalizable to various writing styles and conditions. Before training the models, the collected data undergoes preprocessing. This involves resizing the digit images to a standard dimension and applying augmentation techniques. Data augmentation is critical as it artificially increases the diversity of the training data by creating modified versions of the original dataset, thereby improving the model's ability to generalize to new, unseen data. The preprocessed data is then partitioned into training and test datasets. The training dataset is used to train multiple deep learning models. The following deep learning models have been executed for projects: EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18]. Each of these models has its architecture and strengths, making it valuable to train and compare them to determine the most effective one for the task. Once the models are trained, they are tested and validated using the test dataset. Performance evaluation metrics are then used to compare the models, ensuring that the best-performing model is selected for the final deployment. It encompasses all necessary steps, from capturing hand movements to preprocessing data and training advanced deep learning models, ultimately leading to accurate and reliable digit classification.

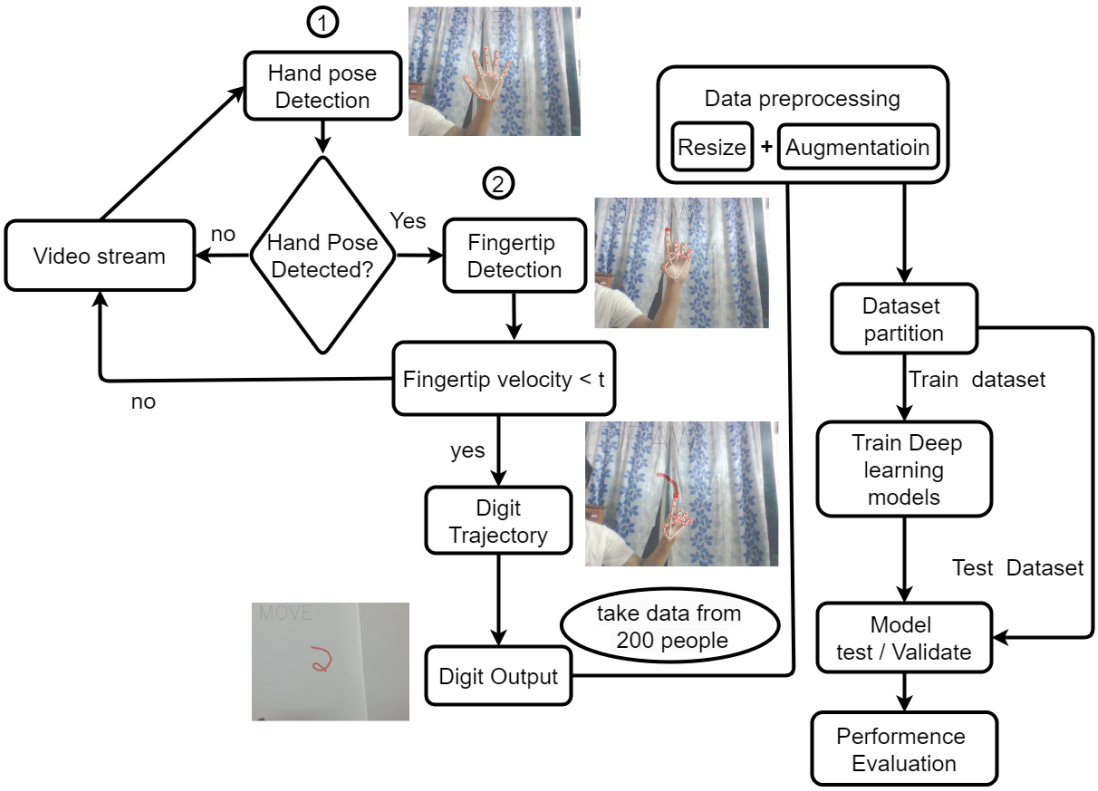


Figure 3.14: The flow diagram of methodology for this research.

3.6 Summary

This chapter of the thesis presents a comprehensive methodology for developing an efficient Bangla digit image classification system using air writing. It outlines the data collection process, gathering diverse samples from various sources, including volunteers performing air writing and synthetic data generation, to ensure a representative dataset. The preprocessing steps involve normalizing the images and converting them into a suitable format for machine learning models. The chapter compares several pretrained models and introduces ensemble techniques to enhance classification performance. This structured approach aims to optimize the accuracy and effectiveness of Bangla digit recognition through air writing, providing a robust foundation for further research and application.

CHAPTER 4

Implementation

4.1 Overview

Outlines the practical steps involved in developing and training models for Bangla digit classification using air writing techniques. It begins with comprehensive data preparation, including dataset collection from various sources, resizing, orientation correction, and augmentation techniques to enhance dataset diversity and model robustness. The chapter then details the selection and configuration of pretrained CNN architectures such EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18]. Each model is adapted for Bangla digit recognition through additional classification layers and fine-tuned using transfer learning from ImageNet.

4.2 Tools & Technologies

The implementation and training of the Bangla digit classification on air writting models utilized a blend of hardware and software to ensure efficient processing and model training. High-performance GPUs were employed to expedite the training of deep learning models. Frameworks and libraries such as TensorFlow [23] and Keras [21] were used for for implementing various deep learning models such as EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18]. Python [19] served as the primary language for scripting and data preprocessing, with OpenCV [20] aiding in various image processing tasks. This integration of advanced hardware and software tools facilitated the efficient creation and training of the Bangla digit classification models.

4.2.1 Hardware

1. **ASUS TUF F15**: This laptop, equipped with an Intel Core i5 11th Gen processor, 16 GB of RAM and a 512 GB SSD, provided the necessary computational power and storage for training deep learning models efficiently.

2. **HP Pavilion 15**: Featuring an Intel Core i5 10th Gen processor, 8 GB of RAM and a 512 GB SSD, this laptop was used for additional processing tasks. The built-in cameras of both laptops were employed for capturing air writing samples, ensuring a diverse and representative dataset.

3. **Google Colab:** Google Colab [24] was employed for building and training the machine learning models. It provided access to a T4 GPU, significantly accelerating model training compared to CPU-only computations.The Google Colab instances are equipped with an Intel Xeon CPU @ 2.20GHz with 1 core and 2 logical processors due to hyper-threading, an NVIDIA Tesla T4 GPU with 2,560 CUDA cores, and 16 GB GDDR6 memory. 320 Tensor Cores, 8.1 TFLOPS single-precision performance, and 320 GB/s memory bandwidth are all offered by the T4. In addition to providing an extra 100 GB of ephemeral storage and 12–16 GB of RAM, Colab also integrates Google Drive for persistent storage.

4.2.2 Software

1. **Python:** Python 3.10.12 [25] was chosen for its versatility and extensive ecosystem of libraries and frameworks in machine learning and data science. Python's simplicity and readability make it an ideal choice for rapid prototyping and development.

2. **Visual Studio Code:** Visual Studio Code was selected as the Integrated Development Environment (IDE) for coding. It provided a streamlined interface for writing, debugging, and executing Python [25] scripts used in data preprocessing and model development.

3. **Jupyter Notebook:** Jupyter Notebook [26] was utilized for conducting data preprocessing tasks. Its interactive environment facilitated exploratory data analysis,

data manipulation, and visualization, which were crucial for preparing the air writing dataset before training.

4.2.3 Packages and Libraries

1. **CV2:** CV2 4.5.4 [20] short for OpenCV (Open Source Computer Vision Library), is a widely-used library in computer vision and image processing. It provides a vast array of functions for tasks such as reading, writing, manipulating, and analyzing images and videos. OpenCV [20] is renowned for its efficiency and versatility in applications ranging from object detection and recognition to facial recognition and augmented reality

2. **numpy:** A core Python [25] library for numerical computation is called NumPy [27]. Large, multi-dimensional arrays and matrices are supported, and a number of mathematical operations are available for effective manipulation of these arrays. Because NumPy [27] is the foundation for so many other libraries in the Python [19] ecosystem, it is necessary for tasks like scientific computing, machine learning, and data analysis.Numpy 1.25.2 have been used for research.

3. **mediapipe:** Google created the Mediapipe 0.10.14 [28] framework, which provides a full range of pre-built tools and machine learning models for creating different kinds of perception-based applications. It makes it easier to create pipelines that process and analyze multimedia data, including audio and video streams. With modules for tasks like pose estimation, object detection, face detection, and hand tracking, Mediapipe [28] is a valuable tool for a variety of computer vision and machine learning applications.

4. **Pillow:** PIL 9.4.0, known as Pillow [29] is a Python library for opening, manipulating, and saving various image file formats. It's used widely in digital art, computer vision, and image processing for tasks like filtering, resizing, and format conversion. In addition to these basic operations, Pillow supports advanced functionalities such as image enhancement, drawing shapes and text, and batch processing of images. Its ease of use and extensive documentation make it a popular choice among developers and researchers for implementing complex image processing pipelines efficiently.

4.3 Dataset Collection

The dataset for Bangla digit on air writting image classification was collected using a custom script that utilizes the MediaPipe [28] library for hand tracking and OpenCV [20] for image processing. The steps involved in the dataset collection are detailed below:

1. **Environment Setup:** The script begins by importing necessary libraries: OpenCV [20] for image processing, NumPy [27] for numerical operations, MediaPipe [28] for hand tracking, and additional utilities for handling files and directories.

```
import cv2
import numpy as np
import mediapipe as mp
import os
```

2. **Hand Tracking Initialization:** MediaPipe's [28] hand tracking solution is initialized to detect and track hand landmarks. This enables capturing the movement and positions of hand joints in real-time.

```
mp_hands = mp.solutions.hands
hands = mp_hands.Hands()
```

3. **Video Capture:** The script captures video from the webcam. Each frame of the video is processed to detect hand landmarks.

```
cap = cv2.VideoCapture(0)
```

4. **Identification of Hand Landmarks:** The core logic involves processing each video frame to detect hand landmarks. If a hand is detected, the landmarks are extracted and normalized to the image dimensions.

```
while cap.isOpened():
    success, image = cap.read()
    if not success:
```

```
        continue

    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    results = hands.process(image)

    if results.multi_hand_landmarks:
        for hand_landmarks in results.multi_hand_landmarks:
            data = [(landmark.x * width, landmark.y *
                height) for landmark in hand_landmarks.
                landmark]
            data = np.array(data)
            # Further processing and mode detection
```

These landmarks are then used to perform specific actions like drawing or moving based on the distance between certain points.

5. **Drawing and Mode Handling:** The script defines various modes such as drawing, erasing, and clearing. These modes are determined by analyzing the hand landmarks and distances between specific points.

```
def draw(src, pt1, pt2):
    if pt1 != (-5000, -5000) and pt2[0] != (-5000, -5000):
        src = cv2.line(src, pt1, pt2, (0, 0, 255), 10)

def clear(src):
    src = cv2.rectangle(src, (0, 0), (width, height), (255,
        255, 255), -1)

def action(digitLength, pt1, pt2, src):
    if digitLength < some_threshold:
        draw(src, pt1, pt2)
    return mode
```

6. **Saving Collected Images:** Collected data is saved when the user presses specific keys. The data includes hand landmarks and the corresponding drawn images. This data is stored in directories named after the collected characters.

```
if k == ord('s'):
```

```
    n_collected += 1
    save_dir = f"./collected_data/{user_name}/{
        collected_char}/"
    if not os.path.isdir(save_dir):
        os.mkdir(save_dir)
    write_data(save_dir, data_history, blended)
    clear(src)
    data_history.clear()
```

7. **Cleanup:** Windows closed for cleanup, data collected, and resources released.

```
hands.close()
cap.release()
cv2.destroyAllWindows()
```

This structured approach allows for systematic collection and organization of the dataset, ensuring that each character's hand movement data is accurately captured and stored for subsequent training and analysis.

4.4 Dataset Preparation

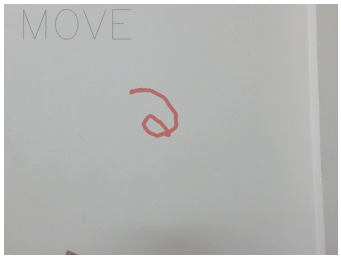
This section outlines the process of preparing the dataset for the Bangla digit classification on air writting project. The dataset consists of a total of 5314 images distributed across 10 classes. Below is the distribution of images per class as shown in Table 4.3

Table 4.3: No. of images for collected Bangla digit.

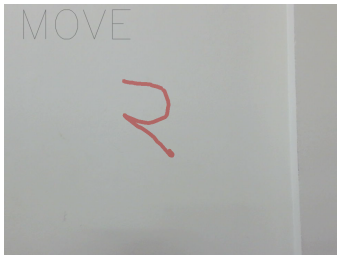
Digit	No. of Bangla digit
0	526
1	534
2	533
3	531
4	532
5	532
6	532
7	533
8	531
9	530

When collecting the dataset, each individual's name was assigned to organize the data. Initially, all data were stored in folders labeled from 0 to 9, corresponding to each digit. Subsequently, data from approximately 200 individuals were consolidated into the 'collected_data' folder, where subfolders 0 through 9 contain data classified by their respective digits. This organizational structure defines the classes used in this study. The Bangla digit on air writing image dataset utilized in our study includes the following pictures shown in Figure 4.15. The preparation involves defining the classes,

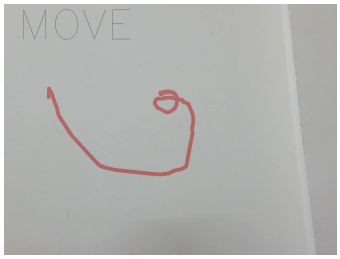
(a) Class: 0



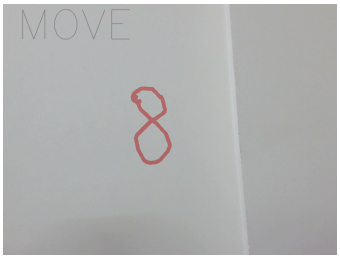
(b) Class: 1



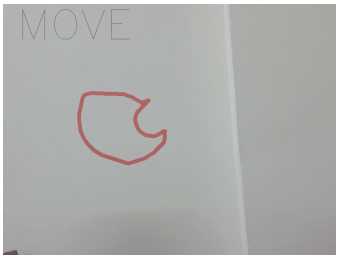
(c) Class: 2



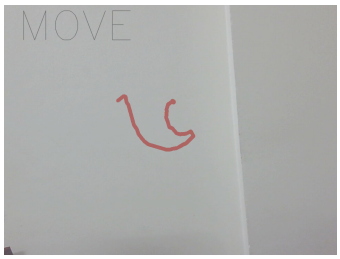
(d) Class: 3



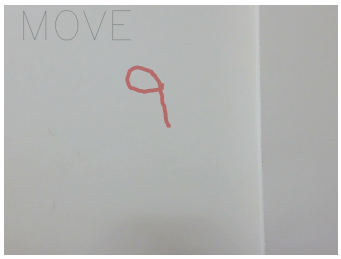
(e) Class: 4



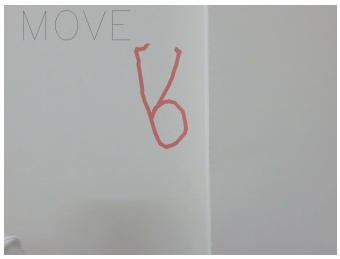
(f) Class: 5



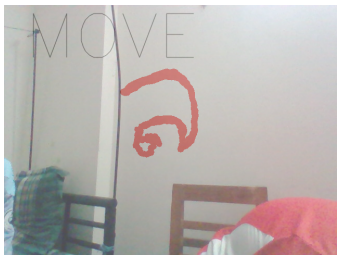
(g) Class: 6



(h) Class: 7



(i) Class: 8



(j) Class: 9

Figure 4.15: Sample images from our dataset.

preprocessing the images, augmenting the data, and dividing the dataset into training, validation, and test sets.

4.4.1 Data Preprocessing

Ensure uniformity and enhance model performance, several preprocessing procedures were implemented on the original images. These included resizing, orientation correction, systematic renaming, and organizing into a well-structured directory. These preprocessing steps are essential for maintaining consistency throughout the dataset, thereby facilitating effective model training and evaluation.

1. **Directory Setup:** This Python [19] script creates a single ”destination_folder” by combining data from multiple folders arranged by class labels (0–9) and individuals. It creates ”destination_folder” if it doesn't already exist after making sure it does. The script traverses through subfolders that match class labels as it iterates through each person folder in ”source_folder”. It ensures that every file is uniquely renamed using the individual's folder name, class label, and unique index when it copies files from each class folder to ”destination_folder”. The combined dataset can be easily accessed and analyzed thanks to this organized method.

```
    import os
import shutil
def merge_data(source_folder, destination_folder):
    if not os.path.exists(destination_folder):
        os.makedirs(destination_folder)

    for person_folder in os.listdir(source_folder):
        person_folder_path = os.path.join(source_folder,
            person_folder)
        if os.path.isdir(person_folder_path):
            for class_folder in range(10):
                class_source_folder = os.path.join(
                    person_folder_path, str(class_folder))
                if os.path.exists(class_source_folder):
```

```
                    for root, dirs, files in os.walk(
                        class_source_folder):
                        for index, file in enumerate(files)
                            :
                            source_file = os.path.join(root
                                , file)
                            destination_file = os.path.join
                                (destination_folder, str(
                                class_folder), f"{
                                person_folder}_{class_folder
                                }_{index}{os.path.splitext(
                                file)[1]}")
                            if not os.path.exists(os.path.
                                dirname(destination_file)):
                                os.makedirs(os.path.dirname
                                    (destination_file))
                            shutil.copy(source_file,
                                destination_file)

# Source folder containing data for each person
source_folder = 'collected_data'
# Destination folder where merged data will be stored
destination_f
merge_data(source_folder, destination_folder)
```

2. **Renaming:** The provided Python [19] script utilizes the os module to systematically rename files within sub-folders labeled from 0 to 9 within the directory "collected_data". It iterates through each sub-folder, checks for the existence of files, and sequentially renames them using a format that combines the sub-folder name and a running index. This ensures that each file is uniquely identified and organized, facilitating better management and analysis of the dataset. The script includes error handling to manage cases where sub-folders or files might be missing, maintaining robustness throughout the renaming process.

```
import os
def change_filenames(directory):
    # Iterate through each sub-folder (0-9)
```

```
    for subdir in range(10):
        subdir_path = os.path.join(directory, str(subdir))
        # Check if the sub-folder exists
        if os.path.exists(subdir_path):
            # Iterate through each file in the sub-folder
            for idx, filename in enumerate(os.listdir(
                subdir_path)):
                # Construct the new filename
                new_filename = f"{subdir}_{idx+1}.jpg"  #
                    Assuming JPG images, change extension
                    accordingly if needed
                # Rename the file
                os.rename(os.path.join(subdir_path,
                    filename), os.path.join(subdir_path,
                    new_filename))
                print(f"Renamed {filename} to {new_filename
                    }")
# Directory where collected_data folder is located
directory = "small_data_1"
change_filenames(directory)
```

3. **Resizing :** The Python [19] script resizes images in an input folder before saving them to an output folder. It use the os module for file operations and PIL [29] for image processing. The resize_images function requires three arguments: ”input_folder”, ”output_folder”, and size (224x224 pixels by default). If the output folder does not already exist, it creates one, and then searches the input folder for picture files. It resizes each image and saves it to the appropriate subfolder in the output folder while preserving the original folder structure. Each scaled image generates a message, which the script prints.

```
    import os
from PIL import Image

def resize_images(input_folder, output_folder, size=(224,
    224)):
    if not os.path.exists(output_folder):
```

```
        os.makedirs(output_folder)

    for subdir, dirs, files in os.walk(input_folder):
        for file in files:
            file_path = os.path.join(subdir, file)
            if file_path.lower().endswith(('png', 'jpg', '
                jpeg', 'bmp', 'gif')):
                with Image.open(file_path) as img:
                    img_resized = img.resize(size, Image.
                        ANTIALIAS)
                    # Create the corresponding output
                        subdirectory
                    relative_path = os.path.relpath(subdir,
                         input_folder)
                    output_subdir = os.path.join(
                        output_folder, relative_path)
                    if not os.path.exists(output_subdir):
                        os.makedirs(output_subdir)
                    output_path = os.path.join(
                        output_subdir, file)
                    img_resized.save(output_path)
                    print(f"Resized and saved: {output_path
                        }")
input_folder = '/content/collected_data'  # Change this to
    your input folder path
output_folder = '/content/resize_collected_data'  # Change
    this to your output folder path
resize_images(input_folder, output_folder)
```

4.4.2 Data Augmentation

Various data augmentation techniques were used to improve the model's capacity to generalize and enrich the dataset. By making altered copies of the original photos, these methods increase the diversity of the dataset. By using this method, the model is able to learn to recognize signs in a greater variety of environmental and situational contexts. The techniques used for augmentation include

```
    train_datagen = ImageDataGenerator(
```

```
    rescale=1./255,
    rotation_range=60,
    width_shift_range=0.5,
    height_shift_range=0.5,
    shear_range=0.5,
    zoom_range=0.5,
    horizontal_flip=True,
)
])
```

1. **Rescale:** Increases the effectiveness of training a model by normalizing pixel values to a range of 0 to 1.

2. **Rotation Range:** Increases image quality and diversifies training samples by randomly rotating them up to 60 degrees.

3. **Width Shift Range:** Broadens dataset variability by horizontally shifting images by up to half their width.

4. **Height Shift Range:** Adjusts images vertically by up to 50%, increasing the diversity of the dataset.

5. **Shear Range:** Increases the robustness of the dataset by introducing shearing transformations up to 50%.

6. **Zoom Range:** Enhances dataset robustness by introducing shearing transformations up to 50%

7. **Zoom Range:** Increases the robustness of the dataset by introducing shearing transformations up to 50%.

8. **Horizontal Flip:** Horizontal image mirroring adds diversity to dataset samples for better generalization.

4.4.3 Data Splitting

The provided code segment splits the dataset into training and validation sets using TensorFlow's [23] "image_dataset_from_directory" function. It loads images from the

directory specified by ”folder_dir_tr”, resizes them to a specified size (SIZE), likely (500x300 pixels), and organizes them into batches for efficient training.

```
    train_set = tf.keras.utils.image_dataset_from_directory(
    directory=folder_dir_tr,
    shuffle=True,
    image_size=SIZE,  # Resize images to 244x244
    batch_size=batch_size,
    label_mode='categorical',
    seed=22,
    validation_split=0.2,  # 20% of the data will be used for
        validation
    subset='training',  # Specify that this is the training set
    interpolation='bilinear'  # Interpolation method for
        resizing
)

validation_set = tf.keras.utils.image_dataset_from_directory(
    directory=folder_dir_tr,
    shuffle=True,
    image_size=SIZE,  # Resize images to 244x244
    batch_size=batch_size,
    label_mode='categorical',
    seed=22,
    validation_split=0.2,  # 20% of the data will be used for
        validation
    subset='validation',  # Specify that this is the validation
        set
    interpolation='bilinear'  # Interpolation method for
        resizing
)
```

1. **Training set:** It uses 80% of the data for training. Images are shuffled ”shuffle=True” to randomize the order in which batches are presented during training. Labels are encoded in the categorical format ”label_mode='categorical' ”.

2. **Validation set:** It uses the remaining 20% of the data ”validation_split=0.2”, ”subset='validation' ” for validation. Similar settings for image resizing, batch-

ing, shuffling, and label encoding apply as in the training set.

3. **Seed:** The seed=22 parameter is used to set a seed value for the random number generator in TensorFlow's [23] "image_dataset_from_directory" function. This ensures reproducibility in data shuffling and batch organization. By setting a specific seed (22 in this case), the random processes involved in shuffling images and organizing batches will produce the same sequence of outputs each time the code is run, provided all other parameters remain unchanged. This is particularly useful for debugging, testing, and ensuring consistent results in machine learning experiments.

4.5 Model Training

Each model (EfficientNetB0 [9], InceptionV3 [10], InceptionResNetV2 [11], MobileNet [12], MobileNetV2 [13], ResNet50 [14], ResNet101 [15], VGG16 [16], VGG19 [17], Xception [18]) was selected for its complex architecture, proven effectiveness in image classification, and adaptability to Bangla digit recognition. We delve into specific architectural details, data augmentation strategies, training configurations, and optimization techniques employed to fine-tune these models for accurate recognition of Bangla digit on air writing.

4.5.1 Experimental Setup

1. **Learning Rate:** Learning rates for the models were set to 0.00001 for EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Xception [18] while Vgg19 [17] used a slightly lower rate of 0.000001. These choices were made to strike a balance between training stability and convergence speed, considering the complexities of each model and the characteristics of the dataset.

```
model.compile(optimizer=tf.keras.optimizers.Adam(1e-5),
    loss='categorical_crossentropy', metrics=['accuracy
    '])
```

```
    model.compile(optimizer=tf.keras.optimizers.Adam(1e-6),
        loss='categorical_crossentropy', metrics=['accuracy
    '])
```

2. **Epoch:** The training of multiple models over 50 epochs is demonstrated by this code snippet, which includes EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18] models. In order to maximize model performance and avoid overfitting, callbacks like checkpointing, early stopping, and learning rate reduction are used to track training progress.

```
    history = model.fit(
    train_generator,
    epochs=50,
    validation_data=validation_generator,
    callbacks=[checkpoint, early_stopping, reduce_lr]
)
```

3. **Image Size:** This configuration indicates that 224 x 224 pixel images were resized for the EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18] models.

```
data_dir = '/kaggle/input/saadnewdataset/dataset'
img_size = (224, 224)
batch_size = 32
```

4. **Weight:** By initializing the model with pre-trained parameters from the ImageNet dataset [30], the 'imagenet' weights improve the model's recognition and feature extraction capabilities from images. This method makes use of in-depth training on a wide variety of objects and scenes, which enables efficient transfer learning for enhanced model performance across a range of computer vision tasks.

```
base_model = EfficientNetB0(weights='imagenet',
    include_top=False, input_shape=(224, 224, 3))
```

5. **Loss function:** The loss function being used is categorical_crossentropy. This loss function is typically used for multi-class classification problems where the labels are one-hot encoded.

```
model.compile(optimizer=tf.keras.optimizers.Adam(1e-5),
     loss='categorical_crossentropy', metrics=['accuracy
    '])
```

6. **Batch Size:** A batch size of 32 was used for all models to ensure stable gradient updates and effective GPU utilization. This balance helps in maintaining computational efficiency and training stability across the models.

```
data_dir = '/kaggle/input/saadnewdataset/dataset'
img_size = (224, 224)
batch_size = 32
```

7. **Optimizer:** The Adam optimizer is a popular choice in deep learning, combining the advantages of two other extensions of stochastic gradient descent: AdaGrad and RMSProp.

```
model.compile(optimizer=tf.keras.optimizers.Adam(1e-5),
     loss='categorical_crossentropy', metrics=['accuracy
    '])
```

```
model.compile(optimizer=tf.keras.optimizers.Adam(1e-6),
     loss='categorical_crossentropy', metrics=['accuracy
    '])
```

It adapts the learning rate for each parameter and uses both first-order and second-order moments of gradients to accelerate convergence. Using a learning rate of 1×10^{-5} or 1×10^{-6}, it ensures fine-tuned adjustments during training, optimizing the categorical_crossentropy loss for multi-class classification tasks.

8. **Regularization:**

   (a) **Early stopping**: The provided code's EarlyStopping callback keeps track of the validation loss (val_loss). To prevent the model from overfitting, it stops the training process if the validation loss does not get better for three consecutive epochs (patience=3).

```
early_stopping = EarlyStopping(monitor='
    val_loss', patience=3, restore_best_weights
    =True)
```

   It maintains the model's optimal state by restoring the weights from the epoch with the best validation performance (restore_best_weights=True), effectively striking a balance between training efficiency and generalization capacity.

   (b) **Dropout**: Increasing the dropout rate to 0.5 means that during training, half of the input units to the dropout layer (x) will be randomly set to zero.

```
x = Dropout(0.5)(x)
```

   This regularization technique helps prevent overfitting by encouraging the network to learn more robust and generalized features.

4.5.2 Load of Pre-trained Models

1. **Xception Model:** Google developed Xception [18]), which stands for "Extreme Inception," a sophisticated convolutional neural network design. By replacing the traditional Inception modules with depthwise separable convolutions, it improves the Inception design and creates a more effective model that performs well in picture classification tasks.

```
base_model = Xception(weights='imagenet', include_top=
    False, input_shape=(224, 224, 3))
```

2. **InceptionV3 Model:** Google unveiled InceptionV3 [10], a complex convolutional neural network architecture with a unique modular structure that allows it

to handle multi-scale information. It achieves the highest performance in a variety of vision tasks and is very effective for large-scale image classification.

```
base_model = InceptionV3(weights='imagenet', include_top=
    False, input_shape=(224, 224, 3))
```

3. **MobilenetV2 Model:** Google created the effective deep learning model MobileNetV2 [13], which makes creative use of linear bottlenecks and

```
base_model = MobileNetV2(weights='imagenet', include_top=
    False, input_shape=(224, 224, 3))
```

inverted residuals for mobile and embedded vision applications. Because of its ability to balance precision and speed, it works well in contexts with limited resources.

4. **Inceptionresnetv2:** With the help of InceptionResNetV2 [11], a potent convolutional neural network architecture, deep learning can be accomplished effectively and efficiently by combining the advantages of residual connections and Inception modules. In comparison to other architectures, this hybrid approach enables the model to achieve high accuracy with comparatively fewer parameters.

```
base_model = Inceptionresnetv2(weights='imagenet',
    include_top=False, input_shape=(224, 224, 3))
```

Its robust performance and versatility make it a popular choice for image classification and other computer vision applications.

5. **Resnet50:** ResNet50 [14] is a 50-layer deep convolutional neural network that is well-known for addressing the vanishing gradient issue by using residual connections. The model can learn identity mappings thanks to these connections, which facilitates the training of extremely deep networks. ResNet50 offers a balance between computational efficiency and depth, making it a highly effective model for image classification and other computer vision tasks.

```
base_model = Resnet50(weights='imagenet', include_top=False
    , input_shape=(224, 224, 3))
```

6. **Resnet101:** With 101 layers, ResNet101 [15] is a deep convolutional neural network that builds upon ResNet50's architecture to enhance performance. It solves the vanishing gradient problem by using residual connections to make training easier by allowing gradients to move through the network more readily. Because of its greater depth, ResNet101 provides higher accuracy in image classification and other computer vision tasks. It is a widely used model.

```
base_model = Resnet101(weights='imagenet', include_top=
    False, input_shape=(224, 224, 3))
```

7. **Vgg16:** The 16-layer convolutional neural network architecture VGG16 [16] is renowned for its consistency and ease of use. It is composed of fully connected layers after a sequence of convolutional layers with tiny 3x3 filters. VGG16 is a well-liked option in the computer vision community because of its high performance in image classification tasks, which is achieved despite its relatively simple design.

```
base_model = Vgg16(weights='imagenet', include_top=False,
    input_shape=(224, 224, 3))
```

8. **Vgg19:** Adding more convolutional layers for improved feature extraction, the VGG19 [17] convolutional neural network architecture has 19 layers and builds upon the VGG16 design. At the end, it has fully connected layers and consistently applies small 3x3 filters to all convolutional layers. Thanks to its deeper architecture, which enables it to detect more intricate patterns in the data, VGG19 is renowned for its excellent performance in image classification tasks.

```
base_model = Vgg19(weights='imagenet', include_top=False,
    input_shape=(224, 224, 3))
```

4.5.3 Model Configuration

To change the complexity of the model, dense layers with 32, 64, or 128 units are used. These dense layers are preceded by a GlobalAveragePooling2D layer, which lowers the input's spatial dimensions. A dropout layer with a rate of 0.5 is used to randomly set

50% of the units to zero during training in order to prevent overfitting. Lastly, the output probabilities for each class are obtained by classifying the data into ten groups using a softmax layer.

```
# Add custom layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(64, activation='relu')(x)  # Reduce the number of
    units
x = Dropout(0.5)(x)  # Increase dropout
predictions = Dense(10, activation='softmax')(x)  # Assuming you
     have 10 classes
# Define the model
model = Model(inputs=base_model.input, outputs=predictions)
```

4.5.4 Training Pre-trained Models

Every pretrained model was initially set to run for 50 epochs, but some of them stopped running early because of early stopping. MobileNet, EfficientNetB0, ResNet50, and ResNet101 all finished all 50 epochs. On the other hand, Xception stopped at 34 epochs, VGG16 at 23 epochs, VGG19 at 39 epochs, MobileNetV2 at 45 epochs, and InceptionV3 at 32 epochs.

```
history = model.fit(
    train_generator,
    epochs=50,
    validation_data=validation_generator,
    callbacks=[checkpoint, early_stopping, reduce_lr]
)
```

4.6 Summary

Illustrates a methodical approach to implementing Bangla digit classification using air writing models, focusing on practical issues and technology tools. By combining Python [19] for scripting, Visual Studio Code for development, and Google Colab for GPU-accelerated training, the chapter demonstrates a strong architecture for fast model

building and optimization. The use of several pretrained models and ensemble techniques highlights the chapter's emphasis on achieving high accuracy and reliability in recognizing Bangla digit images. This implementation builds the groundwork for the upcoming evaluation and validation in Chapter 5, providing vital insights into the topic of machine learning-driven digit recognition.

CHAPTER 5

Result and Analysis

5.1 Overview

A thorough examination of the outcomes produced from multiple deep learning models applied to the Bangla digit image classification job. This offers extensive performance information for each model: EfficientNetB0 [9], InceptionV3 [10], Inceptionresnetv2 [11], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [15], Vgg16 [16], Vgg19 [17], Xception [18]. The study also assesses the effectiveness of various models in improving categorization accuracy. By rigorously comparing different models, the study hopes to uncover the benefits and shortcomings of each strategy, providing insights about the most effective Bangla digit classification strategies.

5.2 Model Performance

Several models that performed exceptionally well in the evaluation of Bangla digit image classification were identified. In evaluating Bangla digit image classification, VGG16 and InceptionResNetV2 stood out with exceptional 99.0% accuracy, showcasing robust feature extraction. InceptionV3 followed closely at 98.53%, leveraging residual network features effectively. Conversely, ResNet50 and VGG19 showed lower accuracy at 96.77% and 97.55%, respectively. EfficientNetB0 and MobileNetV2 achieved good results at 98.02% and 98.45%, demonstrating efficiency without compromising performance. Xception also performed well with 98.45% accuracy, highlighting its suitability for complex image tasks. Overall, VGG16 and InceptionResNetV2 lead in accuracy, while EfficientNetB0, MobileNetV2, and Xception offer efficient alternatives for robust Bangla digit classification. Overall, the study emphasizes how impor-

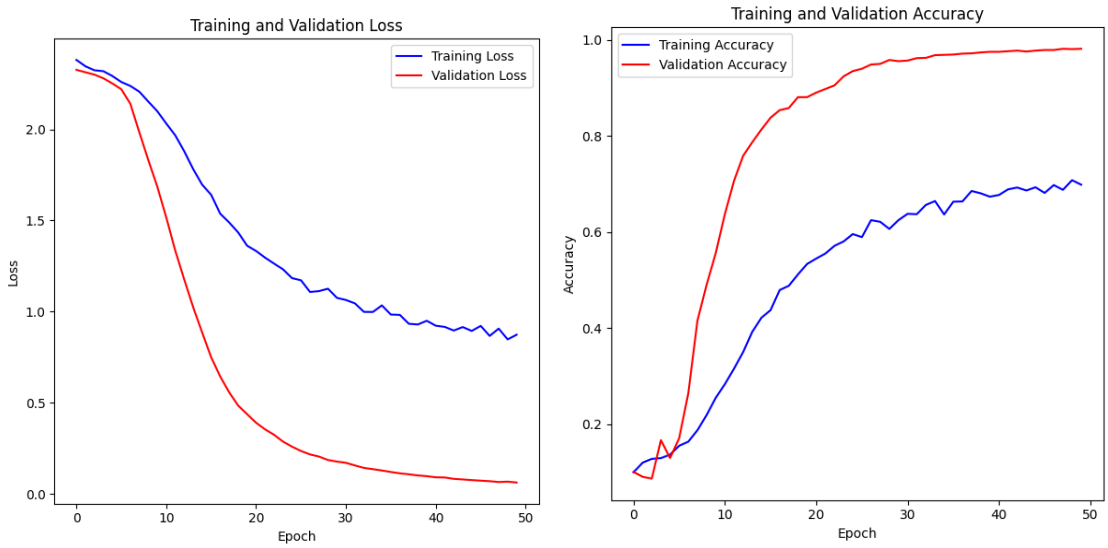
tant model architecture is to obtaining high accuracy in Bangla digit recognition, with VGG16, InceptionResNetV2, and InceptionV3 standing out as the top candidates because of their exceptional ability to capture the fine details that are specific to Bangla digits shown in Table 5.4.

Table 5.4: Performance metrics of various Deep learning models.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
EfficientNetB0	98.02	98.0	98.0	98.0
InceptionV3	98.53	99.0	99.0	99.0
InceptionResNetV2	98.70	99.0	99.0	99.0
MobileNetV2	98.45	98.0	98.0	98.0
ResNet50	97.77	98.0	98.0	98.0
ResNet101	98.47	98.0	98.0	98.0
VGG16	98.90	99.0	99.0	99.0
VGG19	97.55	98.0	98.0	98.0
Xception	98.45	98.0	98.0	98.0

5.3 Loss and Accuracy Curve

1. **EfficienetnetB0:** The model was trained using more than 50 epochs. Less overfitting and effective learning are suggested by the training loss decreasing gradually from 2.5 to 0.5, while the validation loss dropped quickly and stabilized at

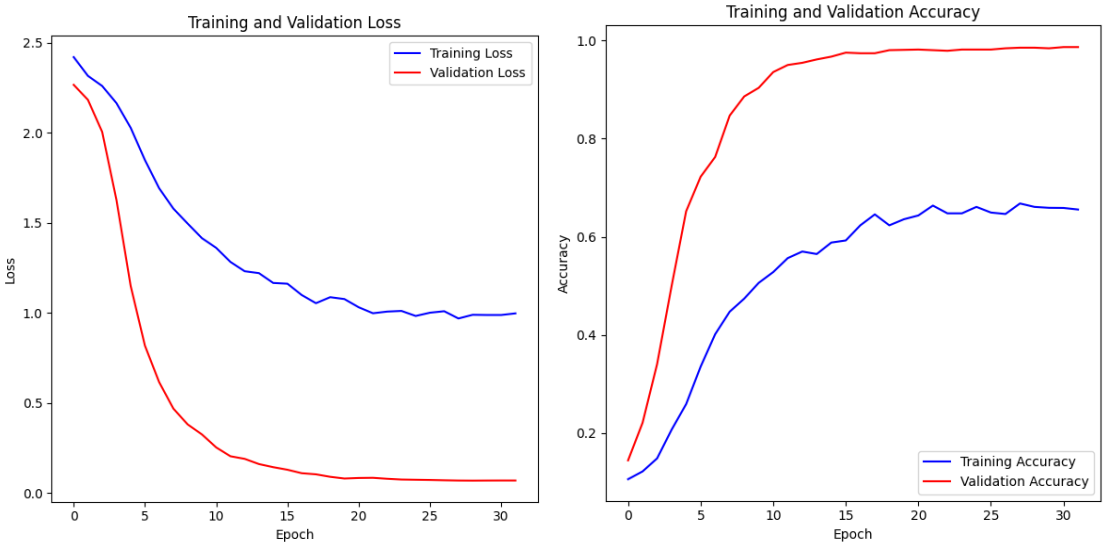


(a) (b)

Figure 5.16: Inceptionv3 model's loss (a) and accuracy (b).

0.1. Training accuracy increased from 10% to 85%, while validation accuracy increased sharply to stabilize at 95%. Strong and stable generalization was shown by the convergence of the accuracy and loss curves when discerning complex patterns in the dataset. This steady performance highlights the model's capacity to identify subtle characteristics, which makes it a good fit for practical uses where dependability and accuracy are crucial. The training process has yielded consistent improvements in both metrics, indicating that the selected architecture and training strategy have been successful in producing high-performance.

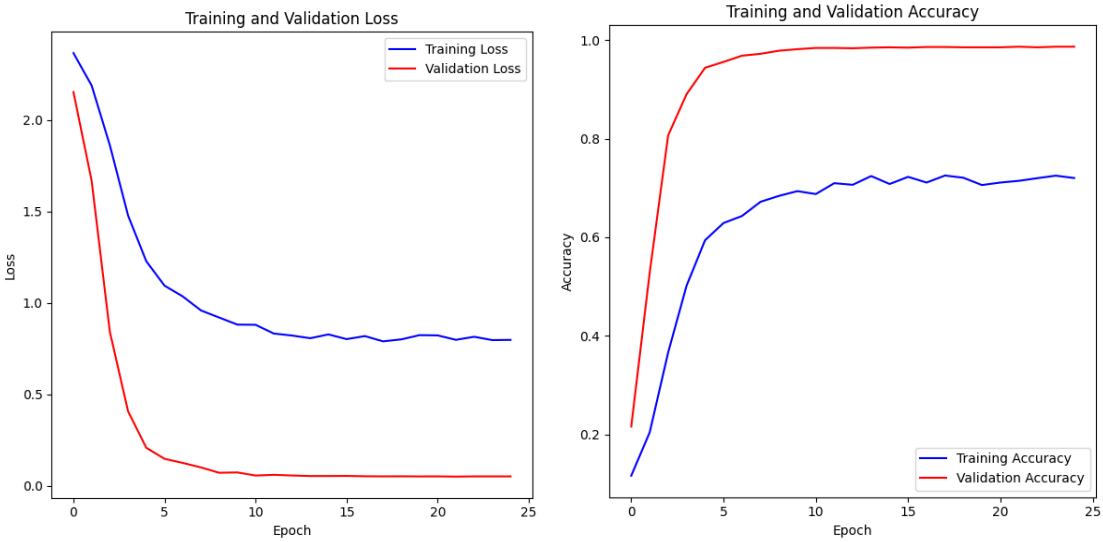
2. **Inceptionv3:** The training and validation curves for the model show its performance over 30 epochs. The training loss begins around 2.5 and gradually falls to around 0.5, whereas the validation loss decreases quickly and stabilizes at around 0.1, showing effective learning and minimal overfitting shown in Figure 5.17.The training accuracy starts around 10% and steadily improves to about 85%, whereas the validation accuracy starts around 10% and rapidly rises to over 95%. The convergence of the loss and accuracy curves, particularly the validation metrics, illustrates the model's durability and ability to transfer effectively to previously encountered data. The little fluctuation toward the curves' ends indicates the model's stability and competence in learning complex patterns from the dataset.



(a) (b)

Figure 5.17: Inceptionv3 model's loss (a) and accuracy (b).

3. **Inceptionresentv2:** The model's training and validation curves show how it performed across 25 epochs shown in Figure 5.18.The training loss begins around 2.5 and gradually falls to around 0.5, whereas the validation loss decreases quickly and stabilizes at around 0.1, showing effective learning and minimal overfitting. While validation accuracy starts at 10% and rapidly surpasses 95%, training accuracy starts at 10% and increases gradually to 85%. The model's robustness and successful generalization to new data are demonstrated by the convergence of the accuracy and loss curves, particularly in validation metrics.

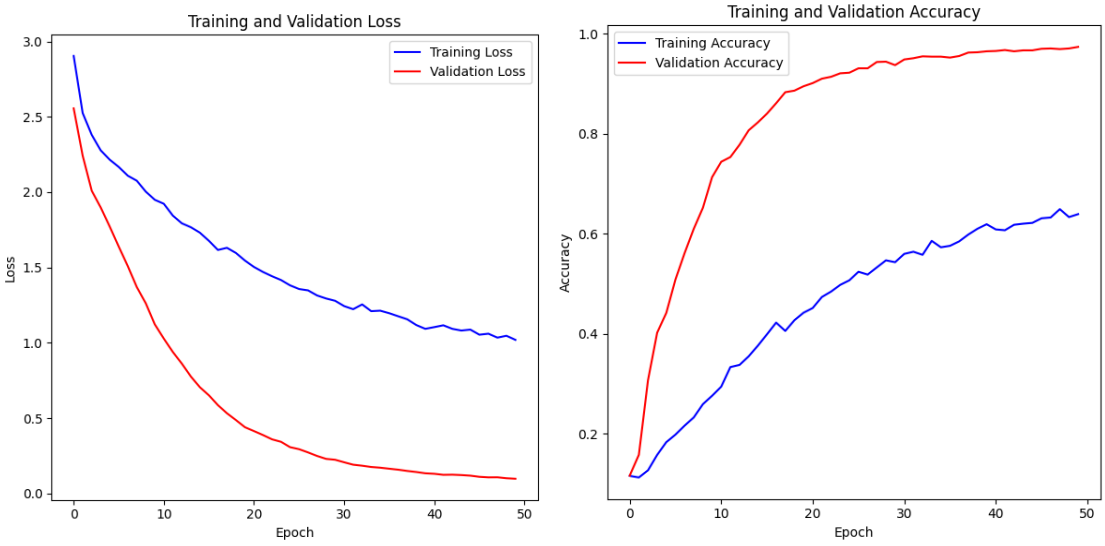


(a) (b)

Figure 5.18: Inceptionresentv2 model's loss (a) and accuracy (b).

4. **Mobilenet:** The provided plots show the training and validation loss and accuracy curves for a MobileNet [12] model over 50 epochs. In the training and validation loss plot (left), the training loss starts high and steadily decreases, indicating that the model is learning and improving its predictions on the training data. The validation loss also decreases significantly in the early epochs and continues to drop until it stabilizes around epoch 30, suggesting the model is improving its generalization to the validation data but begins to plateau. In the training and validation accuracy plot (right), the training accuracy starts low and increases gradually, showing the model is learning to make more accurate predictions on the training data. The validation accuracy starts low as well but rises rapidly, indicating that the model is quickly improving its performance on the validation set, although

it begins to stabilize and show only marginal improvements after a certain point. The gap between the training and validation curves in both plots indicates the extent of overfitting; in this case, the model shows better performance on the validation set initially, but as training progresses, the gap narrows, demonstrating a good fit and generalization.

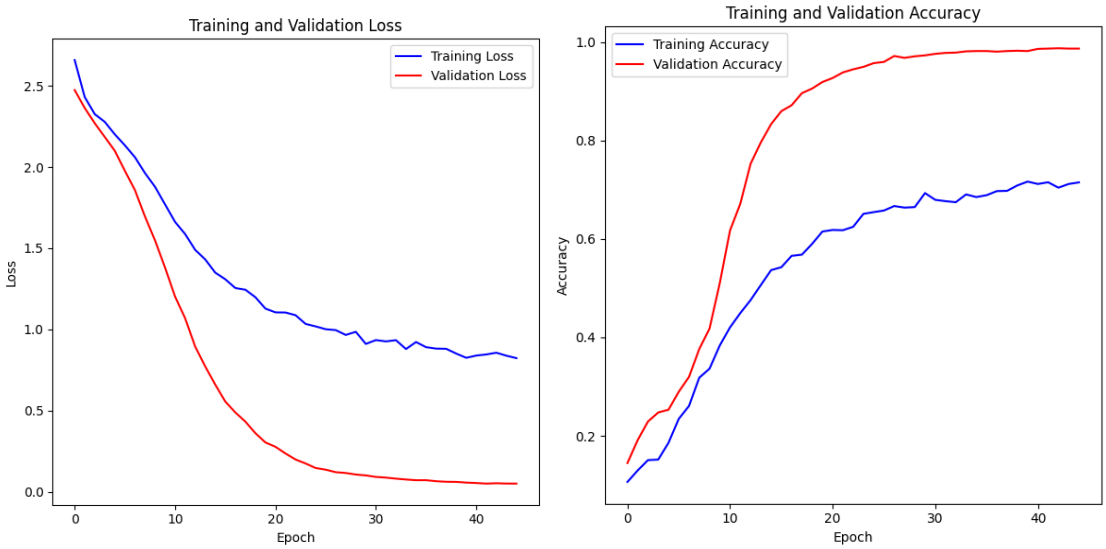


(a) (b)

Figure 5.19: Mobilenet model's loss (a) and accuracy (b).

5. **MobilenetV2:** The Training and Validation curves of the MobileNetV2[13] [13] model show its performance over 45 epochs. Training loss starts at 2.5, drops to 0.5, while validation loss decreases rapidly and stabilizes at 0.1, indicating effective learning with minimal overfitting. The training accuracy starts around 10% and steadily improves to about 85%, whereas the validation accuracy starts around 10% and rapidly rises to over 95%. The convergence of the loss and accuracy curves, particularly the validation metrics, illustrates the model's durability and ability to transfer effectively to previously encountered data. Towards the ends of the curves, there is little fluctuation, demonstrating the model's stability and competence in learning complex patterns from the dataset. These results highlight the robustness and efficiency of MobileNetV2 [13] in handling Bangla digit classification tasks using air writing techniques. Furthermore, the rapid stabilization of the validation loss underscores the model's capacity to generalize well. This efficiency makes MobileNetV2 [13] a suitable choice for real-time

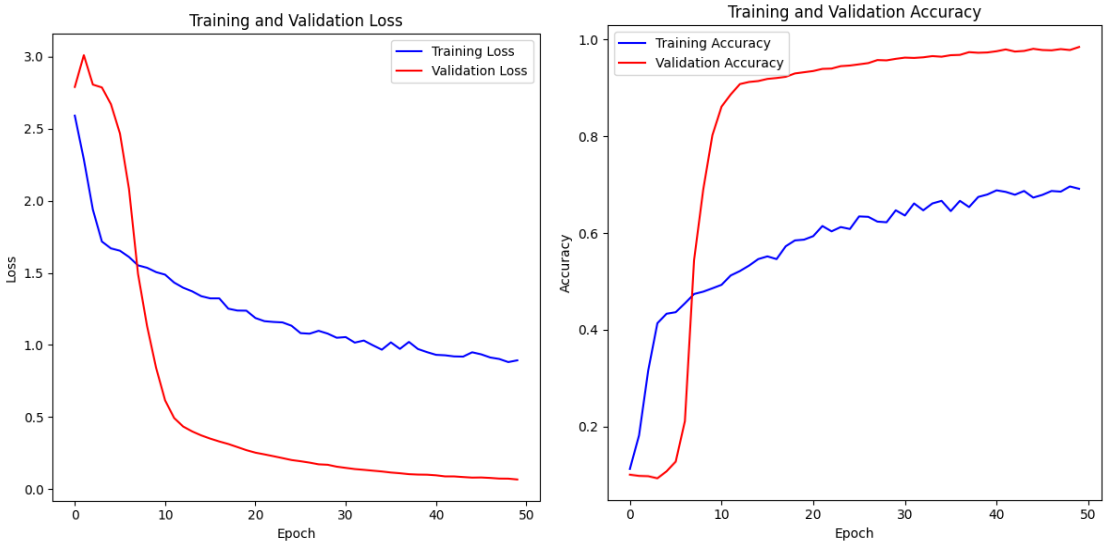
applications where swift and accurate recognition is crucial.



(a) (b)

Figure 5.20: Inceptionresentv2 model's loss (a) and accuracy (b).

6. **Resnet50:** The model's training and validation curves demonstrate its performance across 50 epochs. The training loss begins around 2.5 and gradually falls to around 0.5, whereas the validation loss decreases quickly and stabilizes at around 0.1, showing effective learning and minimal overfitting in Figure 5.21.

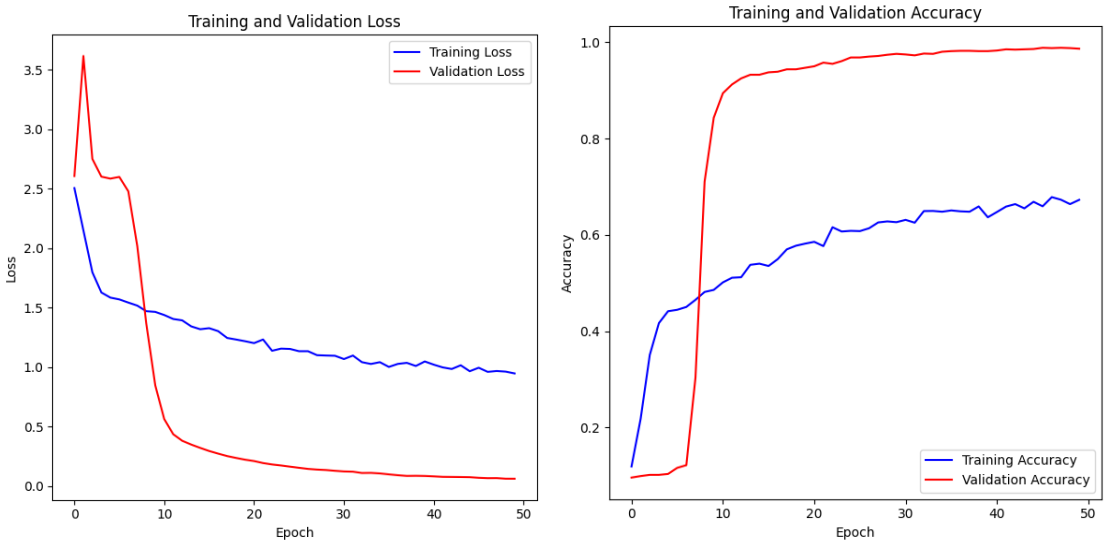


(a) (b)

Figure 5.21: Resnet50 model's loss (a) and accuracy (b).

The training accuracy starts around 10% and steadily improves to about 85%, whereas the validation accuracy starts around 10% and rapidly rises to over 95%. The convergence of the loss and accuracy curves, particularly the validation metrics, illustrates the model's durability and ability to transfer effectively to previously encountered data. These results underscore the robustness and generalization capability of the model in real-world scenarios.

7. **Resnet101:** The training and validation curves for themodel show its performance over 50 epochs shown in Figure 5.22. The training loss begins around 2.5 and gradually decreases to around 0.9, whereas the validation loss rapidly decreases and stabilizes at around 0.1, showing effective learning and minimal overfitting. The training accuracy starts at 0% and steadily improves to around 65%, but the validation accuracy increases rapidly to approximately 97% from 0% at first. The model's robustness and successful transfer to known data are demonstrated by the convergence of the loss and accuracy curves, particularly in validation metrics. The model's steady learning of intricate dataset patterns is reflected in the low volatility near the ends of the curves.

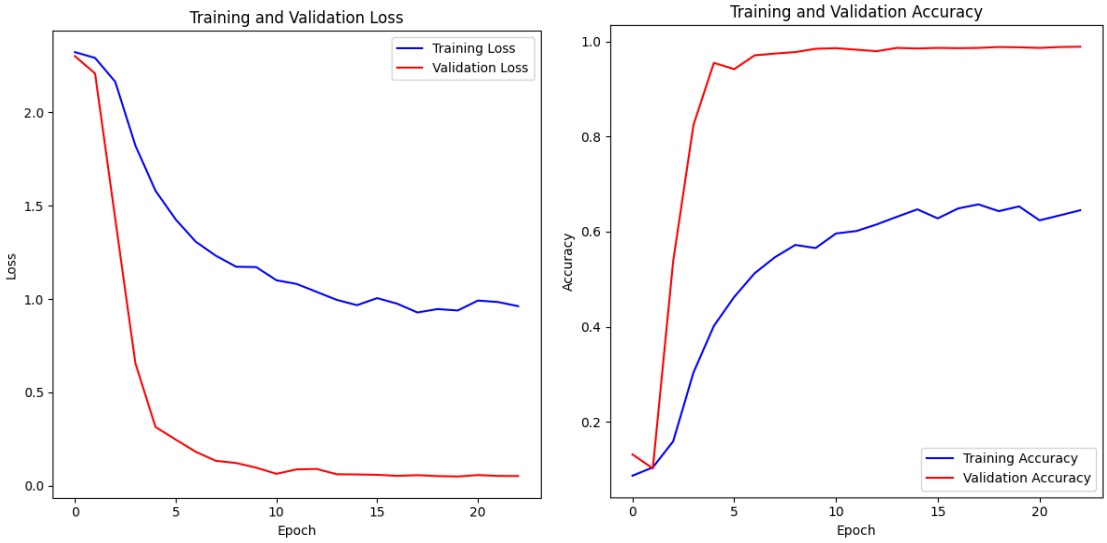


(a) (b)

Figure 5.22: Resnet101 model's loss (a) and accuracy (b).

8. **Vgg16:** The performance of the model over 23 epochs is shown in Figure 5.23. The training loss begins around 2.5 and gradually falls to around 0.5, while the

validation loss decreases quickly and stabilizes at around 0.1, indicating effective learning and minimal overfitting. Training accuracy starts around 10% and steadily improves to about 85%, with validation accuracy starting at 10% and rapidly rising to over 95%. The convergence of the loss and accuracy curves, particularly the validation metrics, illustrates the model's robustness and its ability to effectively generalize to new data. These results underscore the model's reliability and potential for real-world applications in Bangla digit recognition using air writing techniques.The consistent performance throughout the epochs highlights its stability and suitability for deployment in practical settings.

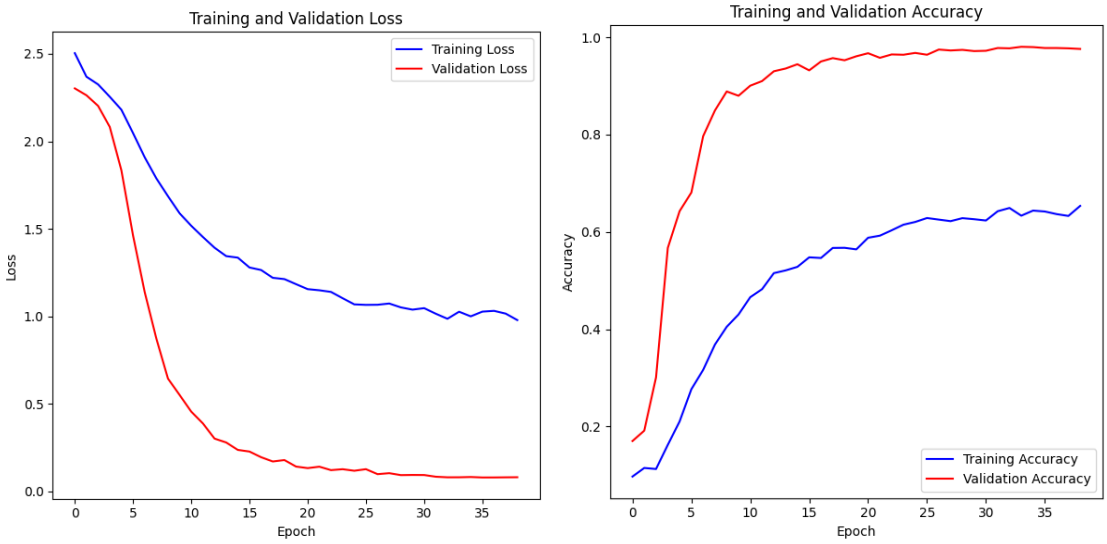


(a) (b)

Figure 5.23: Vgg16 model's loss (a) and accuracy (b).

9. **Vgg19:** The model's training and validation curves show how it performed across 39 epochs, as shown in Figure 5.24. The training loss begins around 2.5 and gradually falls to around 1.0, indicating consistent improvement in the model's learning process. Conversely, the validation loss decreases quickly and stabilizes at around 0.1, showing effective learning and minimal overfitting. The training accuracy starts at approximately 10% and steadily improves to about 55%, reflecting the model's increasing proficiency in recognizing patterns within the training data. Meanwhile, the validation accuracy, which also begins around 10%, rises sharply to approximately 97%, demonstrating the model's robustness and generalization capability to unseen data. These trends suggest that the VGG19 model

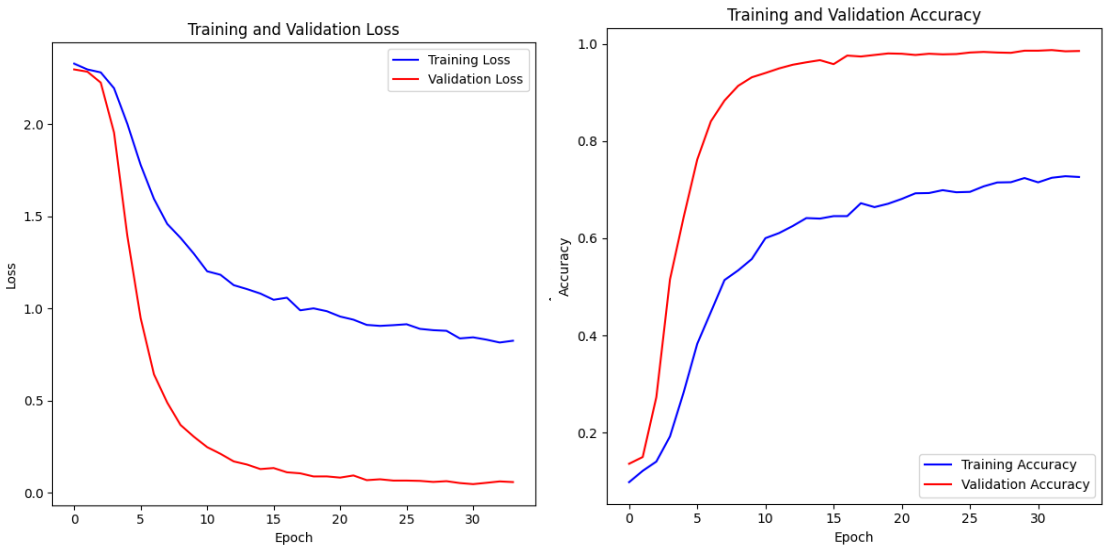
efficiently captures the underlying features of the dataset, balancing learning and generalization.



(a) (b)

Figure 5.24: Vgg19 model's loss (a) and accuracy (b).

10. **Xception:** The training and validation curves for the model show its performance over 34 epochs. The training loss begins around 2.2 and gradually falls to around 1.0, whereas the validation loss rapidly decreases and stabilizes at around 0.1,



(a) (b)

Figure 5.25: Xception model's loss (a) and accuracy (b).

showing effective learning and minimal overfitting. "The training accuracy starts at 5% and rises to 70%, while the validation accuracy starts at 7% and quickly exceeds 97%, as shown in Figure 5.25."

5.4 Result Analysis

5.4.1 Performance comparison

The accuracy of several deep learning models is compared in the bar graph shown in Figure 5.26. With an accuracy of 98.91%, VGG16 [16] stands out the most, closely followed by InceptionV3 [10] at 98.53% and InceptionResNetV2 [11] at 98.70%. Both ResNet101 [15] and MobileNetV2 [13] exhibit high accuracy levels, ranging from 98.46 to 98.48%. With competitive accuracy levels above 97%, EfficientNetB0 [9], Xception [18], and VGG19 [17] continue to outperform MobileNet [12] and ResNet50 [14], which have slightly lower accuracy levels of 97.18% and 97.78%, respectively. The superior accuracy performance of the VGG16 [16], InceptionResNetV2 [11], and InceptionV3 [10] models is demonstrated by this visualization.

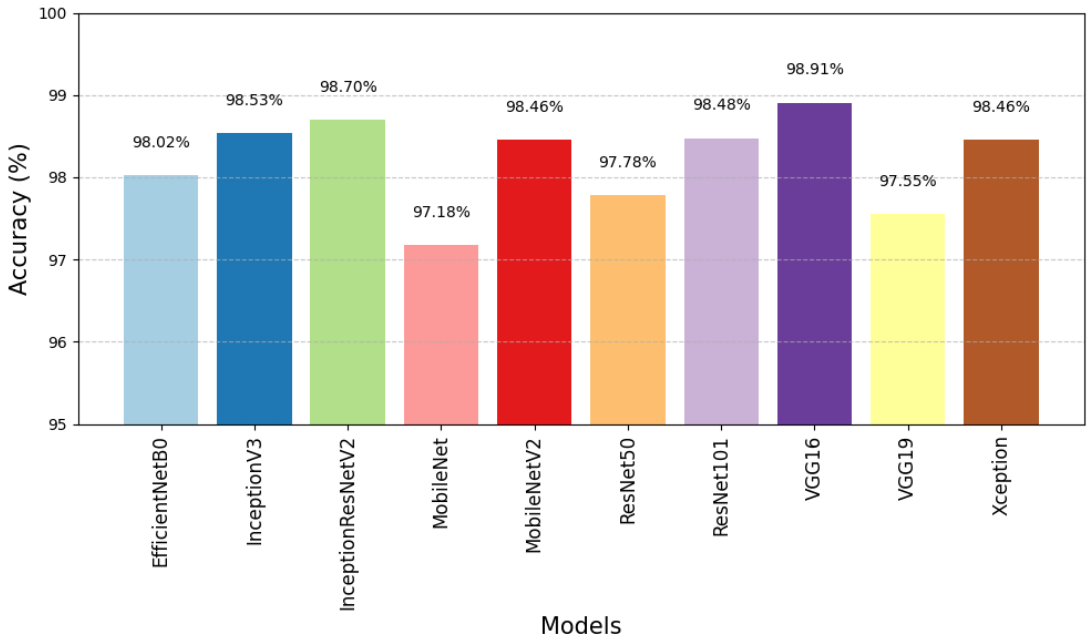


Figure 5.26: Comparison between different models.

5.4.2 AUC-ROC Analysis

Receiver Operating Characteristic Area Under the Curve is referred to as ROC AUC. The performance of the classifier across all potential classification thresholds is summed up by a single figure called the ROC AUC score. You must calculate the area under the ROC curve in order to obtain the score.The classifier's ability to discern between positive and negative classes is indicated by the ROC AUC score. It accepts numbers between 0 and 1 [31]. Plotting TPR against FPR allows AUC-ROC to evaluate classifier performance. True Positive Rate, or TPR, shows accurate positive predictions.

$$\text{TPR} = \frac{\text{True Positives}}{\text{True Positives + False Negative}}$$

False Positive Rate, or FPR, quantifies inaccurately positive predictions.

$$\text{FPR} = \frac{\text{False Positives}}{\text{False Positives + True Negative}}$$

The percentage of real negative cases that the model correctly classifies as negative is known as specificity. It displays the model's capacity to recognize negative examples with accuracy[32].

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative + False Positives}}$$

Given discrete points $(\text{FPR}_i, \text{TPR}_i)$, the AUC can be calculated as:

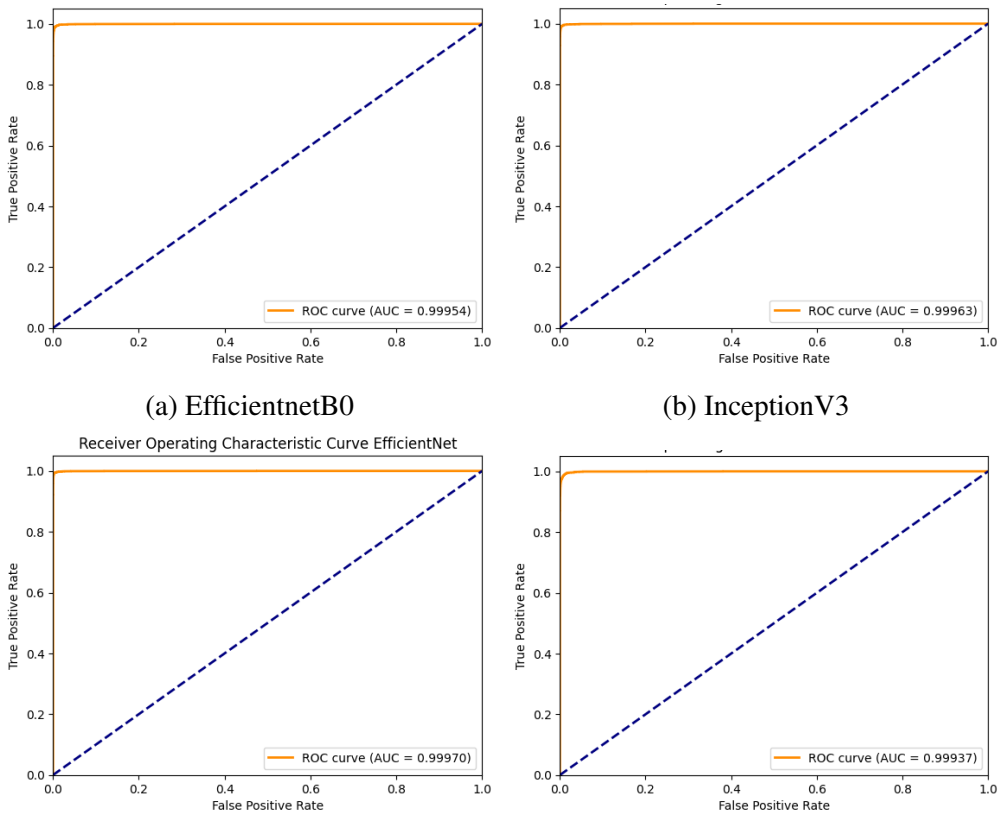
$$\text{AUC} = \sum_{i=1}^{n-1} (\text{FPR}_{i+1} - \text{FPR}_i) \times \frac{\text{TPR}_i + \text{TPR}_{i+1}}{2}$$

The ROC curves and AUC for the ten models we trained will be discussed in this section : EfficientNetB0 achieved an outstanding AUC-ROC score, demonstrating its exceptional accuracy. Similarly, InceptionV3 exhibited high performance, slightly surpassing EfficientNetB0. InceptionResNetV2, while still effective, presented a comparatively lower score. MobileNetV2 maintained competitive performance. Additionally, ResNet50 and ResNet101 achieved remarkable AUC-ROC scores. VGG16 and VGG19 also performed well, demonstrating competitive accuracy in Bangla digit recognition through air writing. Xception excelled with a strong performance, showcasing its ro-

bust capabilities in handling the complexities of the dataset. These results underscore the superior accuracy of EfficientNetB0, InceptionV3, ResNet101, and Xception in recognizing Bangla digits via air writing, highlighting their potential for practical deployment in real-world applications.

5.5 Summary

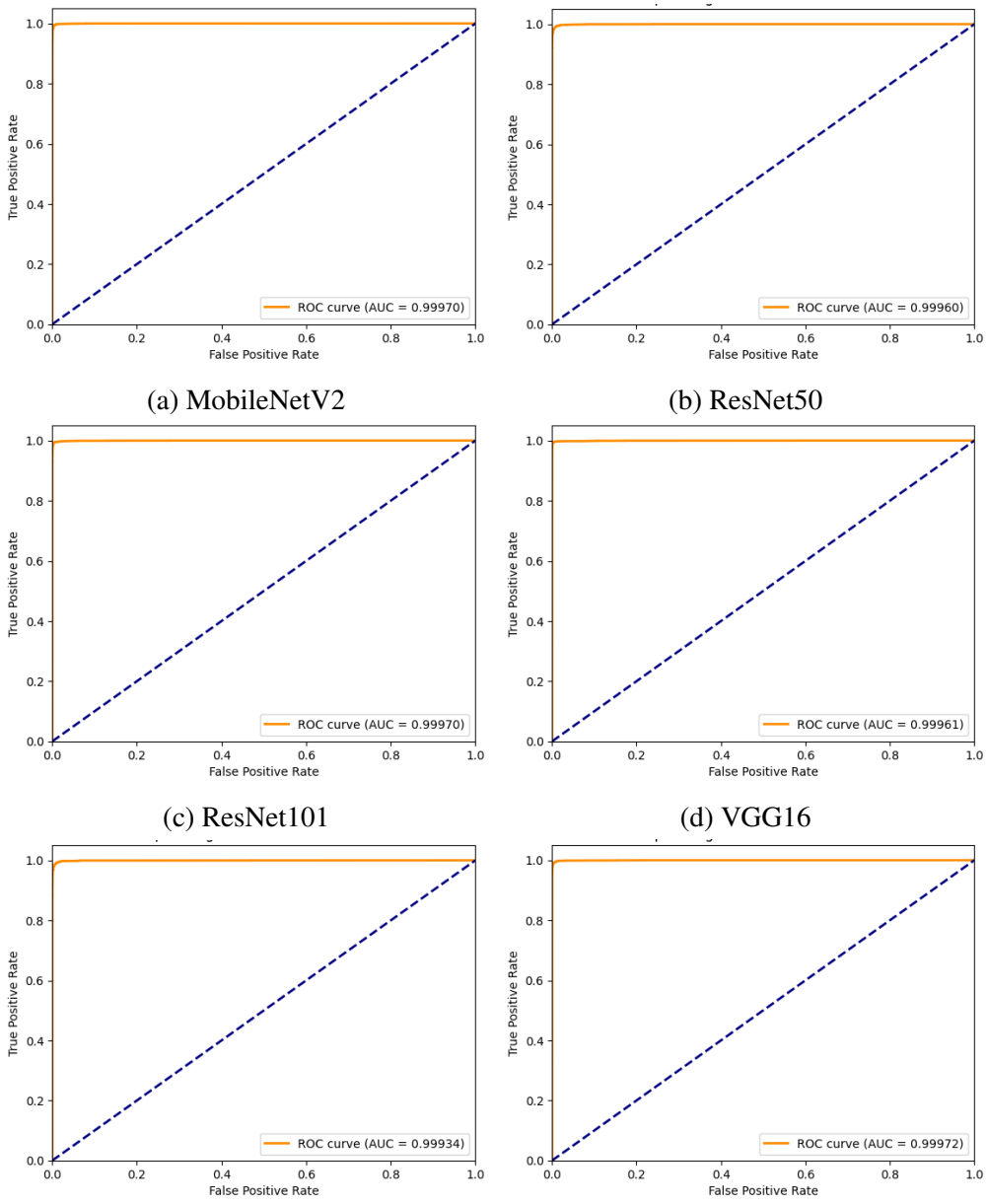
The findings and analysis of the implemented Bangla digit on air-writing recognition models demonstrate their performance measures, such as accuracy and loss patterns throughout epochs. Detailed assessments such as loss and accuracy graphs, AUC-ROC analysis, and confusion matrices are provided. The performance of multiple pretrained models in recognizing Bangla digits is compared, indicating their usefulness and superiority over current datasets. This evaluation demonstrates the effectiveness of custom-designed models in enhancing air-writing digit recognition technology.



(a) EfficientnetB0 (b) InceptionV3

(c) InceptionResNetV2 (d) MobileNet

Figure 5.27: AUC-ROC curves for EfficientnetB0, InceptionV3 , InceptionResNetV2 , MobileNet models.



(a) MobileNetV2 (b) ResNet50

(c) ResNet101 (d) VGG16

(e) VGG19 (f) Xception

Figure 5.28: AUC-ROC curves for Mobilenet, Resnet50, Resnet101, Vgg16, Vgg19, Xception models.

CHAPTER 6

Conclusions and Future Works

6.1 Conclusions

This study creates datasets using a creative method of writing in the air. This thesis aimed to address a significant gap in existing research by creating a comprehensive and diverse dataset of 5314 Bangla digit images contributed by 200 participants. Additionally, this research tackles the challenge of misclassification among visually similar Bangla digit characters, enhancing the accuracy and reliability of digit recognition systems. Previous studies lacked a robust dataset, which limited the effectiveness and accuracy of Bangla digit recognition systems. Python [19] scripts automated data collection and formatted the collected data into a standard 224x224 format, increasing efficiency and repeatability. EfficientNetB0 [9], InceptionV3 [10], Mobilenet [12], Mobilenetv2 [13], Resnet50 [14], Resnet101 [16], Vgg19 [17], Xception [18] were the ten deep learning models that were evaluated. VGG16 [16], and InceptionResNetV2 [11] displayed the best accuracy among them, while MobileNet showed poorer or less accuracy in comparison. This study demonstrates how air writing may be used to build datasets and enhance Bangla script recognition. It has a useful benefit over conventional techniques. The results encourage the development of assistive technology and instructional materials as well as linguistic and cultural diversity in digital applications. Future computer vision research can build on this work, which also emphasizes the value of inclusive datasets in achieving robust model performance in practical scenarios. By expanding datasets to include diverse populations, varying environments, and various numbers, researchers can enhance model generalization and applicability across real-world contexts. This approach not only improves accuracy but also fosters technological advancements that cater to broader societal needs and challenges.

6.2 Future Recommendations

In the future, the following tasks can be performed:

1. Increasing the number of various classes.
2. Increasing the number of images per class.
3. Building lightweight models suitable for our dataset.
4. We can integrate this technology into various applications and real-time tools to broaden its utility and effectiveness

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APPENDIX A

Data Collection :

```
import cv2
import numpy as np
import mediapipe as mp
from enum import Enum, auto
import csv
import datetime
import glob
import copy
import os
import sys

mp_drawing = mp.solutions.drawing_utils
mp_hands = mp.solutions.hands

n_collected = 0

class Mode(Enum):
    """
    """
    DRAW = auto()
    #ERASE = auto()
    #CLEAR = auto()
    MOVE = auto()


def draw(src, pt1, pt2):
    """ This is a function for drawing on an image.
    Args:
        src (numpy.array): Image for drawing
        pt1 (tupple): The starting point of the line to draw
        pt2 (tupple): The ending point of the line to draw
    """
    if pt1 != (-5000, -5000) and pt2[0] != (-5000, -5000):
                src = cv2.line(src, pt1, pt2, (0, 0, 255), 10)


def erase(src, point):
    """ This is a function to erase the lines in the image.
```

```
    Args:
        src (numpy.array): Image for erase the line
        point (tupple): The center point of eraser
    """
    src = cv2.circle(src, point, 100, (255, 255, 255), -1)


def clear(src):
    """ This is a function to make the image blank.
    Args:
        src (numpy.array): Image for clear
    """
    pt1 = (0, 0)
    pt2 = (width, height)
    color = (255, 255, 255)
    src = cv2.rectangle(src, pt1, pt2, color, -1)


def printMode(mode, src):
    """ This is a function to print current mode.
    Args:
        mode (Mode): mode for print
        src (numpy.array): Image for print mode
    """
    #Fill in the text printed in the previous frame.
    src = cv2.rectangle(src, (0, 0), (430, 110), (255, 255, 255), -1)
    #put text in src
    src = cv2.putText(src, mode.name, (40, 100), cv2.FONT_HERSHEY_SIMPLEX, 4, (0,
        0, 0), 1, cv2.LINE_AA)


def action(digitLength, pt1, pt2, src):
    """ This is a function to select a mode and execute it.
    Args:
        digitLength (numpy.array): Used for select a mode
        pt1 (tupple): Used for draw function
        pt2 (tupple): Used for draw function or erase function
        src (numpy.array): Used for all function to draw something.

    Return:
        mode (Mode): return the executed mode
    """
    if digitLength[2] // digitLength[5] < 3 and digitLength[1] // digitLength[5] >
         3:
        mode = Mode.DRAW
        draw(src, pt1, pt2)
    # elif (digitLength[:5] // digitLength[5] < 3).all():
    #     mode = Mode.ERASE
    #     erase(src, pt2)
```

```
    # elif (digitLength[:5] // digitLength[5] > 2).all():
    #     mode = Mode.CLEAR
    #     clear(src)
    else:
        mode = Mode.MOVE
    printMode(mode, src)

    return mode

def write_data(dir_path, data, img):
    with open(dir_path + f'{datetime.datetime.now():%Y%m%d%H%M%S}.csv' , 'w',
        newline="") as f:
        writer = csv.writer(f)
        writer.writerow(['x', 'y'])
        for d in data:
            writer.writerow([d[0], d[1]])
    #cv2.imwrite(dir_path + 'test.jpg', img)
    print(str(n_collected) + " time : " + "complete writing data")

# create save directories
print("please input your name")
user_name = input()
print("What character do you collect?")
collected_char = input()

if not os.path.isdir("./collected_data/" + user_name):
    os.mkdir("./collected_data/" + user_name)
else:
    print("[warning] same user name directory exists")

if not os.path.isdir("./collected_data/" + user_name + '/' + collected_char):
    os.mkdir("./collected_data/" + user_name + '/' + collected_char)
else:
    print("[warning] same character name directory exists")

save_dir = "./collected_data/" + user_name + '/' + collected_char + '/'

# For webcam input:
cap = cv2.VideoCapture(0)
WIDTH: int = 960
HEIGHT: int = 720
cap.set(cv2.CAP_PROP_FRAME_WIDTH, WIDTH)
cap.set(cv2.CAP_PROP_FRAME_HEIGHT, HEIGHT)

data_history = []
pre_mode = None
height, width = 0, 0
# src = cv2.imread('white1.png', -1)
pt1, pt2 = (-5000, -5000), (-5000, -5000)
```

```
134
135
136 #with mp_hands.Hands(min_detection_confidence=0.8, min_tracking_confidence=0.5) as
        hands:
137 hands = mp_hands.Hands(min_detection_confidence=0.8, min_tracking_confidence=0.5)
138 while cap.isOpened():
139     success, image = cap.read()
140     #print(image.shape)
141     if not success:
142         print("Ignoring empty camera frame.")
143         continue
144
145     # Flip the image horizontally for a later selfie-view display, and convert
146     # the BGR image to RGB.
147     image = cv2.cvtColor(cv2.flip(image, 1), cv2.COLOR_BGR2RGB)
148     # To improve performance, optionally mark the image as not writeable to
149     # pass by reference.
150     image.flags.writeable = False
151     results = hands.process(image)
152
153     # Draw the hand annotations on the image.
154     image.flags.writeable = True
155     image = cv2.cvtColor(image, cv2.COLOR_RGB2BGR)
156     if height != image.shape[0] or width != image.shape[1]:
157         height, width = image.shape[:2]
158         print(height, width)
159         src = np.ones((height, width, 3), np.uint8) * 255
160
161
162     if results.multi_hand_landmarks:
163         for hand_landmarks in results.multi_hand_landmarks:
164             mp_drawing.draw_landmarks(
165             image, hand_landmarks, mp_hands.HAND_CONNECTIONS)
166
167             # collect the data
168             data = []
169             for landmark in hand_landmarks.landmark:
170                 data.append((landmark.x * width, landmark.y * height))
171             data = np.array(data)
172
173         digitLength = np.array([[np.linalg.norm(data[i*4][:2] - data[0][:2])] for
                i in range(1,6)])
174         digitLength = np.append(digitLength, np.linalg.norm(data[1][:2] - data
                [0][:2]))
175         pt2 = (int(data[8, 0]), int(data[8, 1]))
176         mode = action(digitLength, pt1, pt2, src)
177         pt1 = pt2
178
179         if mode is Mode.DRAW:
```

```
            data_history.append(pt1)
        #elif mode is not Mode.DRAW and pre_mode is Mode.DRAW: #For double stroke
        #    data_history.append([-1,-1])

        # if mode is Mode.CLEAR:
        #     data_history.clear()

        pre_mode = mode


    blended = cv2.addWeighted(src1=image, alpha=0.7, src2=src, beta=0.3, gamma=0)
    #src[:, :, 3] = np.where(np.all(src == 255, axis=-1), 0, 255)
    cv2.imshow('MediaPipe Hands', blended)

    k = cv2.waitKey(5)
    if k == 27:         # wait for ESC key to exit
        break
    elif k == ord('p'):
        print("What character do you collect?")
        collected_char = input()
        if not os.path.isdir("./collected_data/" + user_name + '/' +
            collected_char):
            os.mkdir("./collected_data/" + user_name + '/' + collected_char)
        else:
            print("[warning] same character name directory exists")
        save_dir = "./collected_data/" + user_name + '/' + collected_char + '/'
        n_collected = 0
        print()
    elif k == ord('c'):
        clear(src)
        data_history.clear()
    elif k == ord('s'): # wait for 's' key to save
        n_collected += 1
        write_data(save_dir, data_history, blended)
        clear(src)
        data_history.clear()
hands.close()
cap.release()
cv2.destroyAllWindows()
```

Collected Data processing:

```
import os
import shutil

def merge_data(source_folder, destination_folder):
    if not os.path.exists(destination_folder):
        os.makedirs(destination_folder)

```

```
    for person_folder in os.listdir(source_folder):
        person_folder_path = os.path.join(source_folder, person_folder)
        if os.path.isdir(person_folder_path):
            for class_folder in range(10):
                class_source_folder = os.path.join(person_folder_path, str(
                    class_folder))
                if os.path.exists(class_source_folder):
                    for root, dirs, files in os.walk(class_source_folder):
                        for index, file in enumerate(files):
                            source_file = os.path.join(root, file)
                            destination_file = os.path.join(destination_folder,
                                str(class_folder), f"{person_folder}_{class_folder
                                }_{index}{os.path.splitext(file)[1]}")
                            if not os.path.exists(os.path.dirname(destination_file
                                )):
                                os.makedirs(os.path.dirname(destination_file))
                            shutil.copy(source_file, destination_file)

# Source folder containing data for each person
source_folder = 'collected_data'
# Destination folder where merged data will be stored
destination_folder = 'merged_data'
merge_data(source_folder, destination_folder)
```

Image Rename:

```
    import os
def change_filenames(directory):
    # Iterate through each sub-folder (0-9)
    for subdir in range(10):
        subdir_path = os.path.join(directory, str(subdir))
        # Check if the sub-folder exists
        if os.path.exists(subdir_path):
            # Iterate through each file in the sub-folder
            for idx, filename in enumerate(os.listdir(subdir_path)):
                # Construct the new filename
                new_filename = f"{subdir}_{idx+1}.jpg"  # Assuming JPG images,
                    change extension accordingly if needed
                # Rename the file
                os.rename(os.path.join(subdir_path, filename), os.path.join(
                    subdir_path, new_filename))
                print(f"Renamed {filename} to {new_filename}")
# Directory where collected_data folder is located
directory = "small_data_1"
change_filenames(directory)
```

Data Loading Function:

```
!pip install -U -q PyDrive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
fid = drive.ListFile({'q':"title='collected_data.zip'"}).GetList()[0]['id']
f = drive.CreateFile({'id': fid})
f.GetContentFile('collected_data.zip')
f.keys()
!unzip collected_data.zip

gpus = tf.config.list_logical_devices('GPU')
stg=tf.distribute.MirroredStrategy(gpus)

import os
from PIL import Image
import matplotlib.pyplot as plt

folder_dir = '/content/collected_data'

# Get the list of folders in the directory
folders = os.listdir(folder_dir)

# Iterate through each folder
for folder in folders:
    # Get the list of images in the current folder
    images = os.listdir(os.path.join(folder_dir, folder))

    # Select the first image from the folder
    if images:
        image_path = os.path.join(folder_dir, folder, images[0])

        # Open the image using PIL
        img = Image.open(image_path)

        # Display the image using matplotlib
        plt.imshow(img)
        plt.title(f'Image from folder {folder}')
        plt.axis('off')  # Hide axis
        plt.show()
```

Data Augmentation:

```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=60,
    width_shift_range=0.5,
    height_shift_range=0.5,
    shear_range=0.5,
    zoom_range=0.5,
    horizontal_flip=True,
    validation_split=0.3  # Increase validation split to 30%
)
```

Model Training:

```
# Define callbacks
checkpoint = ModelCheckpoint('best_model.keras', monitor='val_accuracy',
    save_best_only=True, mode='max')
early_stopping = EarlyStopping(monitor='val_loss', patience=3,
    restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=2, min_lr=1
    e-7)
```

Model Evaluation:

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report, roc_auc_score
    , roc_curve, auc, accuracy_score

# Recheck Data Generators
test_generator = test_datagen.flow_from_directory(
    '/kaggle/input/saadnewdataset/dataset',  # Make sure this directory is correct
    target_size=img_size,
    batch_size=batch_size,
    class_mode='categorical',
    shuffle=False  # Ensure no shuffling for consistency in predictions
)

# 1. Evaluate model on the test set
test_loss, test_acc = model.evaluate(test_generator)
print(f'Test accuracy from evaluate: {test_acc * 100:.2f}%')


# Evaluate the model on test set
```

```
predictions = model.predict(test_generator)
y_true = test_generator.classes
y_pred = np.argmax(predictions, axis=1)

# Calculate accuracy score
accuracy = accuracy_score(y_true, y_pred)
print("Accuracy:", accuracy)

# Generate confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

# Plot confusion matrix using Seaborn
plt.figure(figsize=(15, 15))
sns.heatmap(conf_matrix, annot=True, fmt='g', cmap='Blues')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

# Classification report
print("Classification Report:")
print(classification_report(y_true, y_pred))

# Calculate overall ROC AUC score
roc_auc = roc_auc_score(tf.keras.utils.to_categorical(y_true), predictions,
    average='macro')
print("Overall ROC AUC Score:", roc_auc)

# Plot ROC curve
fpr, tpr, _ = roc_curve(tf.keras.utils.to_categorical(y_true).ravel(), predictions
    .ravel())
roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.5f)' %
    roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Curve EfficientNet')
plt.legend(loc="lower right")
plt.show()

# Plot loss and accuracy per epoch
plt.figure(figsize=(12, 6))

# Plot training loss
plt.subplot(1, 2, 1)
```

```
plt.plot(history.history['loss'], label='Training Loss', color='blue')
plt.plot(history.history['val_loss'], label='Validation Loss', color='red')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Plot training accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Training Accuracy', color='blue')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red'
    )
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```

APPENDIX B

Complex Engineering Problems (CP) and Complex Engineering Activities (CA) Analysis

Title: Bangla Digit Recognition on Air Writing Using Deep Learning Techniques

Attainment of Complex Engineering Problem (CP)

S.L.	CP No.	Attainment	Remarks
1.	P1: Depth of Knowledge Required	Yes	K3 (Engineering Fundamentals): Python described in Chapter 4 Art No: 4.2.2.
			K4 (Engineering Specialization): Knowledge about Deep Learning described in Chapter 3 Art No: 3.4.
			K5 (Design): Methodology flowchart described in Chapter 3 Art No: 3.5.
			K6 (Technology): TensorFlow,image processing, keras,OpenCV etc. described in Chapter 4 Art No: 4.2.
			K8 (Research): Is studying to find the current limitations of existing research in Chapter 2.
2.	P2: Range of Conflicting Requirements	Yes	Dataset scarcity addressed through creation efforts. described in Chapter 4 Art No: 4.3

3.	P3: Depth of Analysis Required	Yes	deeply studied recent research to identify its limitations and developed a comprehensive dataset to address them described in Chapter 2 and Chapter 4 Art No: 4.3 .
4.	P4: Familiarity of Issues	Yes	Writing on the air is not very common. As CSE students, we've worked with this technology described in Chapter 1 .
5.	P5: Extent of Applicable Codes	Yes	applied the standard process of deep learning in Chapter 3.
6.	P6: Extent of Stakeholder Involvement and Conflicting Requirements	Yes	Researchers, individuals with disabilities, and the education sector are involved as stakeholders described in Chapter 1 Art No: 1.7.
7.	P7: Interdependence	Yes	applied standard process of deep learning described in Chapter 3 Art No: 3.3 .

Mapping of Complex Engineering Activities (CA)

S.L.	**CA No.**	**Attainment**	**Remarks**
1.	A1: Range of resources	Yes	Technology such as Keras, TensorFlow, deep learning models, and image processing has been used for this describe in Chapter 3 Art No: 3.2 and 3.4
2.	A2: Level of interaction	Yes	Various challenges encountered during this thesis work described in Chapter 1 Art No: 1.6.
3.	A3: Innovation	Yes	Building a new dataset and model for recognizing Bangla digits on air writing described in Chapter 3 and Chapter 4.

4.	A4: Consequences for Society and the Environment	Yes	enhances accessibility, promotes interactive learning, and supports Bangla language preservation described in Chapter 1 Art No: 1.5.
5.	A5: Familiarity	Yes	The current tasks involve limitations in datasets, prompting the creation of a comprehensive dataset described in Chapter 2 and Chapter 4.

BIOGRAPHY

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Md. Yeamin Islam Sakib

Md. Yeamin Islam Sakib has a strong drive to succeed academically, which stokes his intense interest in computer science and engineering. Born into a family that places a high emphasis on education, Sakib has always strived for academic achievement. Sakib has an excellent academic record and is currently enrolled in the Bangladesh Army University of Science and Technology, Saidpur, Nilphamari, where he is pursuing a B.Sc. in Computer Science and Engineering. Sakib received flawless GPAs of 5.00 for both his HSC at Rajuk Uttara Model College and his SSC at Safiuddin Sarker Academy and College. Sakib's academic journey is complemented by his active participation in various technical workshops, seminars, and competitions. Sakib has developed a keen interest in Software development, Cybersecurity, and Machine learning. Sakib's leadership and practical skills highlight his potential as a future leader in the field. Sakib's dedication and hard work are making a meaningful impact in Computer Science and Engineering.

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Harishankar Barman's journey in Computer Science and Engineering is marked by his passion for learning, academic excellence, and a drive to make a positive impact. Born to Karuna Kanto Barman and Chandana Rani, he grew up in a family that values education and curiosity.Currently pursuing a B.Sc. in Computer Science and Engineering at Bangladesh Army University of Science and Technology, Saidpur, Nilphamary. Hari laid a strong educational foundation with perfect GPAs of 5.00 in both his SSC from Afan Ullah High School, Rangpur, and his HSC from Police Lines School and College, Rangpur. Harishankar is actively engaged in research in Parallel Computing, Machine Learning, Deep Learning, Natural Language Processing, and Image Processing. His work showcases his commitment to advancing technology and solving complex problems. Beyond academics, Harishankar is a dynamic individual contributing to research and extracurricular activities. His leadership skills and practical application of knowledge highlight his role as a future leader in the field. Harishankar's journey reflects his dedication, hard work, and a commitment to excellence, making a meaningful impact in Computer Science and Engineering.

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Musharrat Binte Alam Mithy, born in Rangpur, is the daughter of Md. Mohashin Alam and Selina Akhter. She is a dedicated computer science enthusiast and researcher. She is pursuing her B.Sc. Engineering in Computer Science and Engineering from Bangladesh Army University of Science and Technology, Saidpur, Nilphamari. She completed her SSC from Cantonment Public School and College, Rangpur with GPA 5.00 and HSC from Cantonment Public School and College, Rangpur with GPA 5.00. In academics, Mithy has demonstrated her commitment to advancing knowledge through her research endeavors. She is actively engaged in research in the field of Parallel Computing, Machine Learning and Deep learning.

Mithy played an important work in her thesis research Enhancing Search Efficiency for Large Linked Lists with Multithreading and Caching. Her other works through academics showed her proficiency in Python, Google Colab, Keras, TensorFlow, architectures to built websites and web applications.

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