BANGLADESHI INDIGENOUS GROUP IDENTIFICATION USING DEEP LEARNING APPROACH

BY

SAKHWAT HOSAN
ID: 201-15-13731

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised By

Mushfiqur Rahman
Lecturer (Sr. Scale)
Department of CSE
Daffodil International University

Co-Supervised By

Md Atik Asif Khan Akash
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled "**Bangladeshi Indigenous Group Identification Using Deep Learning Approach**", submitted by **Sakhwat Hosan (ID: 201-15-13731)** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14 July, 2024.

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Department of Computer Science and Engineering
Jahangirnagar University

DECLARATION

I hereby declare that this project has been done by me under the supervision of **Mushfiqur Rahman, Senior Lecturer, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Mushfiqur Rahman
Lecturer (Sr. Scale)
Department of CSE
Daffodil International University

Co-Supervised by:

13/07/24

Md Atik Asif Khan Akash
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Sakhwat Hosan
ID:- 201-15-13731
Department of CSE
Daffodil International University

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ABSTRACT

This study presents a general investigation into the identification of two prominent indigenous groups in Bangladesh, namely the “Chakma (চাকমা)” and “Marma (মারমা)”, by the application of convolutional neural networks (CNNs). This work used some Python-based CNN algorithm and an accompanying web application capable of nearly accurately recognizing indigenous individuals. The research dataset comprised 664 facial images, with 328 belonging to the Chakma group and 336 to the Marma group. The primary objective was to evaluate and identify through comparing the performance of various CNN models, including ResNet50, VGG16, InceptionV3, and DenseNet121, in processing these image datasets. Among the tested models, ResNet50 emerged as the most proficient, achieving a Training Accuracy of 95.85% and a Test Accuracy of 95.52%. These results underscore the exceptional efficiency and adaptability of ResNet50 for the task of indigenous group identification. On the other hand, DenseNet121 got the highest accuracy in training is 97.92%. But test accuracy is lower than ResNet50, that is 86.57%. Beyond the technical aspects, the project also explores the potential applications of indigenous group identification, including preservation of cultural heritage, anthropological research, social justice and human rights advocacy, healthcare and public services customization, educational representation, forensic identification and customized services and products development. By shedding light on the utilization of deep learning techniques for indigenous group identification, this research contributes to both the academic understanding of computer vision applications and the practical implications for various societal sectors. Moreover, the developed web application provides a tangible tool for the recognition and acknowledgment of Bangladesh's diverse indigenous communities.

Keywords: *indigenous group identification, image processing, deep learning, face recognition, CNN, Facial image dataset, ethnicity.*

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CHAPTER 1

INTRODUCTION

1.1 Overview

In a landscape shaped by cultural diversity and societal complexity, the recognition and preservation of indigenous identities stand as very important. Within the rich tapestry of Bangladesh's cultural heritage, the Chakma and Marma communities embody distinct traditions, languages, and ways of life that warrant careful acknowledgment and appreciation. This thesis embarks on a pioneering journey to leverage cutting-edge deep learning techniques, specifically convolutional neural networks (CNNs), in the identification of these two indigenous groups from facial images. The significance of this endeavor lies not only in its technological innovation but also in its profound societal implications. Traditional methods of identifying indigenous groups can be laborious, prone to bias, and lacking in accuracy. However, the advent of deep learning offers a promising avenue for automating this process, transcending the limitations of conventional approaches. By meticulously curating a dataset comprising 664 facial images, with 328 representing the Chakma group and 336 the Marma group, this study sets the stage for a rigorous evaluation of various CNN models. Through meticulous experimentation and analysis, this research aims to assess the performance of prominent CNN architectures, including ResNet50, VGG16, InceptionV3, and DenseNet121, in accurately identifying Chakma and Marma individuals. The findings of this investigation not only shed light on the efficacy of these models but also underscore the exceptional adaptability of deep learning in addressing nuanced societal challenges. Beyond its technical contributions, this thesis delves into the multifaceted implications of indigenous group identification. From the preservation of cultural heritage to the promotion of social justice and human rights, the applications of this research are vast and far-reaching. By fostering a deeper understanding and recognition of Bangladesh's indigenous communities, this project strives to promote inclusivity, diversity, and mutual respect in a rapidly evolving world.

1.2 Background and Present State

Bangladesh is a country rich in cultural diversity, home to numerous indigenous groups that contribute to its vibrant heritage. Among these groups, the Chakma and Marma communities stand out with their unique languages, traditions, and ways of life. These communities are primarily located in the Chittagong Hill Tracts, a region known for its cultural mosaic and historical significance. The preservation of their distinct identities is essential for maintaining the cultural fabric of the nation.Historically, identifying indigenous groups has relied on manual methods that are often subjective and prone to biases. These traditional techniques involve extensive fieldwork, interviews, and observations, which can be time-consuming and inconsistent. Moreover, the accuracy of such methods can be compromised by the personal biases of those conducting the identification, leading to potential misclassification and loss of cultural integrity.

In recent years, technological advancements have provided new tools to address these challenges. The advent of deep learning, a subset of artificial intelligence, has revolutionized various fields, including image recognition and classification. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable capabilities in analyzing and identifying patterns within images, making them a promising solution for the task of identifying indigenous groups from facial images. This thesis aims to harness the power of CNNs to develop an automated system for accurately identifying individuals from the Chakma and Marma communities. By creating a dataset of facial images and employing various CNN architectures, this research seeks to overcome the limitations of traditional identification methods. The study not only aims to enhance the accuracy and efficiency of indigenous group identification but also to contribute to the broader goal of preserving the cultural heritage of Bangladesh.

1.3 Problem Statement

The identification of indigenous groups in Bangladesh, specifically the Chakma and Marma communities, has traditionally relied on manual methods that are often inefficient, subjective, and prone to errors. These conventional approaches involve fieldwork, interviews, and visual inspections, which can be inconsistent and biased due to the personal judgments of those conducting the identification. The manual nature of these processes also makes them time-consuming and impractical for large-scale application, limiting their effectiveness in accurately and consistently identifying individuals from these communities. The inherent subjectivity and potential biases in traditional identification methods pose significant challenges. Misclassification can lead to the erosion of cultural identities and hinder efforts to preserve the unique heritage of these indigenous groups. Moreover, the lack of accuracy and efficiency in these methods can impact various social, administrative, and legal processes that rely on accurate identification.

In contrast, the advent of deep learning technologies, particularly Convolutional Neural Networks (CNNs), offers a promising alternative. CNNs have shown exceptional performance in image recognition tasks, providing a means to automate and enhance the identification process. However, the application of CNNs to the specific context of identifying Chakma and Marma individuals from facial images presents several challenges. These include the need to curate a representative dataset, selecting and fine-tuning appropriate CNN architectures, and ensuring the model's accuracy and reliability in distinguishing between the two groups despite potential variations in facial features, expressions, and image quality. This research aims to address these challenges by developing an automated system using CNNs for the identification of Chakma and Marma individuals. The primary problem this thesis seeks to solve is the inefficiency, inaccuracy, and subjectivity of traditional identification methods. By leveraging deep learning techniques, this study aims to create a robust, objective, and scalable solution that can accurately identify individuals from these indigenous communities, thereby supporting efforts to preserve their cultural identities and improving the reliability of identification processes.

1.4 Objectives

The primary objective of this work is to evaluate the effectiveness of deep learning techniques, specifically Convolutional Neural Networks (CNNs), in the automated identification of Chakma and Marma individuals from facial images. The detailed objectives are :

Dataset Creation

1. Compile a comprehensive dataset of 664 facial images, with 328 images representing the Chakma community and 336 images representing the Marma community.

Model Training and Fine-Tuning

1. Train various CNN models, including ResNet50, VGG16, InceptionV3, and DenseNet121, on the curated dataset.
2. Fine-tune these models to optimize their performance for the specific task of identifying Chakma and Marma individuals.

Performance Evaluation

1. Assess the performance of each CNN model using metrics such as accuracy, precision, recall, and F1-score.
2. Compare the models to determine the most effective architecture for this identification task.

Analysis of Results

1. Analyze the results to gain insights into the strengths and weaknesses of each model.
2. Investigate any misclassifications to understand potential areas for improvement.

Application and Implications

1. Explore the broader applications of the developed system in preserving cultural heritage, enhancing social justice, and supporting human rights.
2. Discuss the potential societal impacts and ethical considerations of using deep learning for indigenous group identification.

Future Directions

1. Identify areas for future research, including expanding the dataset, improving model accuracy, and addressing ethical concerns.
2. Suggest ways to adapt and apply the developed system to other indigenous groups and contexts.

These objectives aim to provide a comprehensive framework for leveraging deep learning to address the challenges of indigenous group identification, thereby contributing to both technological advancement and cultural preservation.

1.5 Scope and Limitations

This thesis focuses on the use of deep learning techniques, specifically Convolutional Neural Networks (CNNs), to automate the identification of Chakma and Marma individuals from facial images. Curating a dataset of 664 facial images, with 328 representing the Chakma community and 336 representing the Marma community, to serve as the foundation for training and evaluating CNN models. Implementing and fine-tuning various CNN architectures, including ResNet50, VGG16, InceptionV3, and DenseNet121, to determine their effectiveness in distinguishing between Chakma and Marma individuals. Assessing the performance of the selected models using standard evaluation metrics such as accuracy, precision, recall, and F1-score to identify the most effective architecture for this task. Analyzing the results to understand the strengths and weaknesses of each model, identifying patterns in misclassifications, and drawing conclusions about the applicability of CNNs for this identification task. Despite the comprehensive scope, this research is subject to several limitations. The dataset comprises 664 images, which, while significant, may not fully capture the diversity and variability within the Chakma and Marma communities. A larger and more diverse dataset could improve the robustness and generalizability of the models. The use of facial recognition technology raises ethical concerns, including privacy issues, potential misuse, and biases inherent in the models. Addressing these concerns requires careful consideration and the establishment of ethical guidelines to ensure responsible use of the technology. Training and fine-tuning CNN models require significant computational resources. Limited access to high-performance computing infrastructure could constrain the ability to experiment with larger models or more extensive hyperparameter tuning.

1.6 Report Organization

Introduction : This section sets the stage for the research by providing an overview of what the paper aims to achieve.

Literature Review : This section explores what others have done! It dives into existing research on our topic, summarizing key findings, models, and methods used by different researchers.

Data Collection : This section details how we'll gather the data: form, field visit, etc.

Data Preprocessing : This section describes how data is prepared for the model.

Research Methodology : Here's how we'll apply the data to answer our research questions and make the model.

Experimental Result and Discussion : In this section we'll discuss our experimental result.

Impact on Society, Environment : This refers to how our research findings might influence people's lives, policies, or social structures and this exploration might affect the environment.

Conclusion and Future Work : In summary we'll wrap up the key findings, and future analysis for next steps.

References : Lists of all references used in this work.

1.7 Summary

This thesis explores the use of deep learning, specifically Convolutional Neural Networks (CNNs), to identify individuals from the Chakma and Marma indigenous communities in Bangladesh. Traditional identification methods are often laborious and biased, lacking accuracy. By curating a dataset of 664 facial images and evaluating various CNN architectures, the research aims to develop a more efficient and accurate identification system. This study not only addresses technological innovation but also underscores the importance of cultural preservation and social justice, offering a significant advancement in the field of automated identification.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The literature review section of this thesis examines 18 research papers published between 2016 and 2024. These papers focus on several key areas relevant to this study. Numerous papers explore advancements in facial recognition technologies, particularly the application of CNNs and their efficacy in various contexts. These studies provide a foundation for understanding the technical aspects of deep learning models used in this research. Some of the reviewed literature addresses methods and challenges in identifying indigenous groups, highlighting the limitations of traditional approaches and the potential of automated systems. Research papers also discuss the broader implications of using technology for cultural preservation, emphasizing the importance of accurate identification in maintaining cultural heritage and promoting social justice. The review includes studies that explore the ethical implications of using facial recognition technology, focusing on privacy concerns, potential biases, and the need for ethical guidelines. Through a comprehensive analysis of these studies, the literature review provides a contextual background for the current research, identifying gaps in existing methods and underscoring the significance of developing an automated, accurate, and ethical system for indigenous group identification.

2.2 Related Works

In recent years, advancements in computer vision and deep learning have revolutionized various fields, including face recognition and ethnicity identification. The ability to accurately determine the ethnicity of individuals based on facial features holds significant implications for security, surveillance, and diverse applications. This review sets the stage for exploring a collection of studies focusing on ethnicity classification using deep learning approaches. From proposing novel methodologies to evaluating performance on specialized hardware, these studies contribute to advancing the frontier of ethnicity identification in face recognition. Each study brings unique insights, methodologies, and datasets, collectively enriching our understanding and capabilities in this critical domain.

Kalkatawi and Saeed (2024) contribute to the field of ethnicity classification using facial images by introducing a deep learning approach. Recognizing the significance of physical appearance, particularly facial traits, in delineating race and ethnicity, the study addresses the challenge of automatically detecting human ethnicity using computer vision techniques. They highlight the limitations of current methodologies, which primarily rely on encoded facial feature descriptors or Convolutional Neural Network (CNN) based feature extractors. In response, the authors propose leveraging deep learning techniques, specifically vision transformers, for a more comprehensive solution. The implementation of Multi-Axis Vision Transformer marks a pioneering effort in this direction, achieving a notable 77.2% classification accuracy across six ethnic groups: Asian, Black, Indian, Latino Hispanic, Middle Eastern, and White. This research signifies a significant advancement in the field, demonstrating the potential of deep learning methodologies to enhance ethnicity recognition in computer vision applications.[1]

Abdulwahid (2023) addresses the pressing issue of ethnic conflicts and the resulting violations of human rights and socio-political instability. Recognizing the importance of ethnicity in shaping individuals' experiences and safety, the study focuses on advancing ethnicity classification using efficient convolutional neural network (CNN) models. Emphasizing the significance of softer biometrics such as race in addition to traditional person recognition, the research explores recent advancements in ethnicity categorization. Specifically, the study contrasts the performance of two distinct CNN models, emphasizing the utilization of the central portion of the face for classification. Employing holdout testing on the MORPH and FERET datasets, the study achieves notable results, with Model A achieving an 85% accuracy and Model B achieving an 86% accuracy in classifying individuals into four ethnic classes. This research underscores the potential of leveraging CNN models for ethnicity classification, particularly in enhancing video surveillance systems and facilitating picture-search queries.[2]

Devaraj et al. (2021) contribute to the advancement of ethnicity recognition through facial feature detection, leveraging deep learning techniques. Recognizing the pivotal role of facial feature discovery in ethnic group recognition, the study underscores the significant progress facilitated by recent developments in deep learning methods. The researchers propose a deep learning model tailored for ethnicity recognition, emphasizing the importance of considering specific facial features characteristic of different ethnical groups. To this end, they curate a dataset comprising Southeast Asian, East Asian, Black, White, Latin, Indian, and Middle Eastern ethnic groups, capturing real-time face images to ensure representativeness. Given the diverse geographical origins influencing facial characteristics, the study adopts a comprehensive approach by collecting data from various regions. Through deep learning-based ethnicity identification, the research aims to elucidate the relationship between ethnicity and ethnic groups, analyzing images with different intensity and registered range. Training on a substantial dataset of 85,000 images, the study achieves precise results, thereby contributing to the understanding of facial feature evolution in anthropology. This research signifies a significant step forward in ethnicity recognition, offering insights into the complex interplay between ethnicity and facial features across diverse populations.[3]

Heng et al. (2018) address the crucial task of ethnicity classification using face images, recognizing ethnicity as a fundamental aspect of human identity with diverse applications, including video surveillance and targeted advertisement. While Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in visual recognition tasks, existing CNN-based approaches for ethnicity classification encounter significant limitations. These include the scarcity of face datasets containing ethnicity information and the treatment of ethnicity classification as a multi-class problem without leveraging the rich hierarchical features inherent in CNNs. To overcome these challenges, the study proposes a hybrid supervised learning method that harnesses both CNN strengths and rich network features. This approach integrates the soft likelihood of CNN classification with an image ranking engine, utilizing hierarchical feature matching between query and dataset images. Through supervised Support Vector Machine (SVM) hybrid learning, the method achieves improved ethnicity classification performance compared to state-of-the-art approaches, demonstrating up to a 3% increase in recognition accuracy. By evaluating the proposed method on a dataset comprising Bangladeshi, Chinese, and Indian ethnicity groups, the study underscores the potential of hybrid supervised deep learning in advancing ethnicity classification using face images.[4]

Wang et al. (2016) contribute to the field of ethnicity classification by proposing a novel approach leveraging Deep Convolutional Neural Networks (CNNs). Recognizing ethnicity as a fundamental attribute in biometric recognition, the study addresses the challenge of ethnicity classification through simultaneous feature extraction and classification using CNNs. Unlike traditional methods that involve separate stages of feature extraction and classifier training, the proposed approach integrates these processes within the CNN framework. The study evaluates the efficacy of the method across three scenarios: the classification of black and white people, Chinese and Non-Chinese individuals, and Han, Uyghurs, and Non-Chinese ethnic groups. Through experiments conducted on both public and self-collected databases, the proposed method demonstrates effectiveness in ethnicity classification, underscoring the potential of Deep Convolutional Neural Networks in addressing this critical task.[5]

Batsukh and Tsend (2016) present a novel computer model designed for effectively extracting nationality from frontal face images. The study emphasizes the importance of considering factors such as face part color, size, and distances in nationality recognition, acknowledging the influence of variables such as image quality, lighting conditions, rotation angle, occlusion, and facial emotion. To address these complexities, the proposed model follows a multi-step approach, beginning with face detection, followed by image conversion and feature extraction, including gender determination, face shape analysis, and identification of key facial points. Subsequently, the model compares these features with a reference database to determine nationality. Notably, the study highlights significant differences observed in samples based on gender and face shapes during measurement. It is essential for input images to be frontal face images with smooth lighting and no rotation angle to ensure accurate results. The applicability of the model extends across various sectors, including military, police, defense, healthcare, and technology. Overall, the study underscores the potential of computer models in distinguishing nationality from facial images, offering valuable insights for applications in diverse fields.[6]

Al-Humaidan et al. (2021) contribute to the field of ethnicity classification by focusing on Arab ethnicity classification using facial images, leveraging deep learning approaches. Recognizing the increasing attention on facial features as soft biometrics for enhancing recognition performance and search engine algorithms for face images, the study addresses the notable absence of research on the Arab world and the lack of Arab-specific datasets. To bridge this gap, the authors aim to create an Arab dataset with proper labeling of Arab sub-ethnic groups, including Gulf Cooperation Council countries (GCC), the Levant, and Egyptian. They employ supervised deep learning, utilizing a Convolutional Neural Network (CNN) pre-trained model, to achieve classification. Additionally, the study explores the application of unsupervised deep learning, specifically deep clustering, for ethnicity classification, marking the first instance of such an approach in this context. Experimental results demonstrate the effectiveness of the proposed methods, with the best accuracy achieved by training a pre-trained CNN on the full Arab dataset and evaluating on a different dataset, reaching 56.97%. Deep clustering methods yield promising results, with accuracy ranging from 32% to 59%, and NMI and ARI scores ranging from zero to 0.2714 and 0.2543, respectively. Overall, this research significantly contributes to advancing ethnicity classification using facial images within the Arab context, offering valuable insights and methodologies for further exploration in this domain.[7]

AlBdairi et al. (2020) contribute to the field of face recognition by addressing the critical task of identifying ethnicity of people through facial features using a deep convolutional neural network (CNN) approach. Recognizing the burgeoning interest in face recognition studies, the researchers highlight the importance of ethnic identification as a significant challenge in this domain. They introduce a new deep learning CNN model specifically designed to recognize the ethnic of people, leveraging a newly curated dataset comprising 3141 images from three different nationalities. Notably, this dataset represents the first collection for the ethnicity of people, which will be made available to the research community. The study compares the performance of the proposed model with two state-of-the-art models, VGG and Inception V3, evaluating validation accuracy for each CNN. Through rigorous testing on multiple images, the results demonstrate the superior performance of the proposed model, achieving a verification accuracy of 96.9%. This research marks a significant advancement in ethnicity identification through facial recognition, offering a novel methodology and dataset for further exploration in this area.[8]

Hamdi et al. (2020) contribute to the field of facial recognition by conducting a comparative study between machine learning and deep learning methods for age, gender, and ethnicity identification. Recognizing the increasing utilization of facial recognition in real-world applications, the study focuses on the automatic classification of age, gender, and ethnicity, which play crucial roles in social interactions. Leveraging the UTKFace dataset, which includes labels for age, gender, and ethnicity, the researchers compare the performance of various machine learning and deep learning techniques. Machine learning methods yield test accuracies of up to 58.04% for age, 86.25% for gender, and 72.78% for ethnicity. Transfer learning enhances performance, achieving 63.53%, 89.14%, and 72.39% accuracy for age, gender, and ethnicity, respectively. The authors propose novel CNN architectures, which outperform previous results, achieving 65.92%, 90.3%, and 78.88% accuracy, with further improvement in age prediction by introducing three classes (Child, Teenager, and Adult) instead of five, reaching 80.46% accuracy. This research contributes to advancing age, gender, and ethnicity identification through facial images, offering insights into the efficacy of different machine and deep learning approaches in this domain.[9]

Alotaibi (2022) addresses the critical task of human ethnicity prediction using facial features, with a focus on creating practical applications for human identification in security settings, particularly at immigration offices. Recognizing the complex nature of facial patterns and the computational challenges inherent in automatic identification, the study proposes an automated approach comprising pre-processing, feature extraction, and classification stages. Face detection is performed using the Viola-Jones algorithm, followed by feature extraction encompassing color, texture, forehead area, and an improved active appearance model (AAM) based on unique features. These extracted features are then fed into an optimized convolutional neural network (CNN) for ethnicity classification. A novel contribution lies in the training of the CNN model using the proposed Moth Spiral adopted Grey Wolf Algorithm (MSGWA) to optimize weights effectively. The performance of the proposed method is evaluated against existing approaches using various metrics including NPV, sensitivity, accuracy, specificity, precision, MCC, and F1-score. This research contributes to advancing ethnicity prediction using facial features, offering a comprehensive methodology and algorithmic optimization approach for enhanced performance in real-world applications.[10]

Zhao et al. (2019) contribute to the domain of face recognition by focusing on Chinese Ethnic Face Recognition (CEFR) using deep learning methods. Acknowledging the significant advancements facilitated by convolutional neural networks (CNNs) in face recognition, the study addresses the practical demands and applications of CEFR in a multi-ethnic country like China. Initially, the authors provide an overview of the face recognition procedure based on deep learning methods. They then highlight the absence of a corresponding dataset for CEFR and address this gap by constructing the Chinese Ethnic Face Images (CCEFI) dataset, encompassing ethnic groups such as Han, Uygur, Tibetan, and Mongolian. Leveraging multi-task cascaded convolution networks (MTCNN) and residual networks (ResNets), the proposed model achieves promising results for both face detection and classification, with an average precision of 75% on the CCEFI dataset. Experimental findings demonstrate the model's capability to detect faces in constrained environments and accurately classify them into their respective ethnic categories. Additionally, the dataset curated by the authors serves as a valuable resource for future research in CEFR and related fields. This research significantly contributes to advancing CEFR using deep learning methodologies, offering insights and resources for further exploration in this domain.[11]

Chacua et al. (2019) contribute to the field of facial recognition by addressing the practical applications of this technology in security-related contexts, such as Closed Circuit Television (CCTV) monitoring systems and access control. Unlike other biometric techniques, facial recognition allows for remote identification, enabling its integration into various institutions to restrict access to unauthorized individuals and prevent property damage and losses. The study focuses on identifying people within a university building plagued by security issues, utilizing a convolutional neural network

(CNN) architecture implemented on a GPU. The methodology comprises three phases: training, learning, and classification. Training of the CNN model is conducted using the VGGFace2 dataset, while learning involves generating discriminatory facial embeddings using softmax loss and center loss signals. Classification is performed using a support vector machine (SVM) across various experiments with different numbers of classes. The effectiveness of the approach is evaluated in real-time on a sample of 128 students, with quantitative metrics derived from confusion matrices. The study reports an overall accuracy of 96% in controlled environments and 71.43% in uncontrolled contexts. These results highlight the potential of the proposed method as a foundation for developing more robust facial recognition systems in production environments, offering promising prospects for enhancing security measures in various settings.[12]

Hamim et al. (2022) contribute to the field of nationality detection by developing an intelligent monitoring model based on deep learning for determining gender and nationality from frontal facial images. Acknowledging the various factors influencing face recognition, such as picture quality, illumination, rotation angle, occlusion, and facial expression, the study emphasizes the importance of recognizing input images accurately before processing them further. The proposed model involves face detection, followed by determination of facial shape, gender, and nationality of the candidate image. Results are derived from distance comparisons using a library for sample measurement. Notably, significant discrepancies are observed across photographs based on gender and facial features during sample measurement. The study highlights the requirement for input images to be frontal faces with clean lighting and no blemishes at any rotation angle. The model's applicability extends to ordinary individuals, models, celebrities, actors, and others, offering a convenient means of nationality detection through facial images. This research contributes to advancing nationality detection using deep learning methodologies, offering insights for various real-world applications requiring authentication and identification based on facial features.[13]

AlBdairi et al. (2022) address the challenging task of ethnicity identification in face recognition (FR) through the development of a novel classification method using machine learning (ML) tools. Recognizing the increasing interest in addressing complex computer vision (CV) problems, particularly in FR, the study introduces a deep learning (DL) approach based on a Deep Convolutional Neural Network (DCNN) model. This model significantly enhances the accurate determination of ethnicity based on facial features. However, due to the computational demands of DCNN-based FR systems, specialized high-performance computing (HPC) hardware is required. The study explores the use of field-programmable gate arrays (FPGAs) to improve the efficiency of the network in terms of power usage and execution time. Experimental evaluation compares the performance of the DCNN-based FR method using FPGAs against graphics processing units (GPUs), utilizing an image dataset comprising 3141 photographs of citizens from three distinct countries. Remarkably, this dataset represents the first collection specifically gathered for ethnicity identification. Additionally, the ethnicity dataset is made publicly available, contributing to the research community. The experimental results demonstrate the high performance of the proposed DCNN model using FPGAs, achieving an accuracy level of 96.9% and an F1 score of 94.6%, while consuming a reasonable amount of energy and hardware resources. This research advances ethnicity identification in FR, offering insights into hardware acceleration techniques and dataset contributions for future research in this domain.[14]

2.3 Comparison Between Existing Works

This study provides a comprehensive comparative analysis of various studies dedicated to ethnicity classification using facial images. The studies employ a range of algorithms, showcasing the versatility of deep learning methodologies in addressing this task. Notable algorithms include convolutional neural networks (CNNs), Multi-Axis Vision Transformer, hybrid supervised learning methods, and deep clustering approaches. While some studies achieve commendable accuracy levels, others do not explicitly mention accuracy metrics, suggesting a variance in reporting standards across the field. Each study contributes distinct methodologies, such as the proposal of a Multi-Axis Vision Transformer or the development of a hybrid supervised learning method, demonstrating tailored approaches to tackle the challenges inherent in ethnicity classification. Moreover, several studies emphasize the creation of specialized datasets, such as the Arab dataset or the Chinese Ethnic Face Images dataset, underscoring the importance of curated data in model training and evaluation. This comparative analysis highlights the diversity of approaches and methodologies within the field, indicating ongoing efforts to advance ethnicity classification using facial images.

Table 2.1: Comparative Analysis with Previous Work

SL	**Author Name**	**Used Algorithm**	**Best Accuracy**
1.	Kalkatawi and Saeed [1]	Multi-Axis Vision Transformer	77.2%
2.	Abdulwahid [2]	Custom CNN	85% and 86%
3.	Al-Humaidan and Prince[7]	Pre-trained CNN, Deep Clustering Methods	56.97% and 32% to 59%
4.	AlBdairi, Xiao, and Alghaili [8]	Deep convolutional neural network (CNN)	96.9%
5.	Hamdi and Moussaoui [9]	CNN	78.88%
6.	Zhao et al. [10]	ResNets	75%
7.	Chacua et al. [11]	Convolutional Neural Network (CNN)	96%
8.	AlBdairi et al. [12]	DCNN	96.9%

2.4 Open Issues

The issues in finishing this work revolves around the details of facial recognition technology applied to indigenous group identification. Completing the work presents several challenges that must be addressed to ensure the success of the project. One significant challenge is the diversity within the facial features of the Chakma and Marma groups. Additionally, acquiring a diverse and representative dataset of facial images for training the models is challenging, as it requires extensive fieldwork in different regions where these indigenous groups reside. Selecting and fine-tuning the appropriate deep learning algorithms, such as ResNet50, VGG16, InceptionV3, and DenseNet121, adds complexity to the project. Each algorithm has its strengths and weaknesses, and determines which one performs best for indigenous group identification demands through experimentation and analysis. Addressing these challenges requires a comprehensive approach that combines technical expertise, ethical considerations, and cultural sensitivity to develop a deep learning model that accurately identifies Chakma and Marma individuals while upholding ethical standards and respecting cultural diversity.

2.5 Summary

Literature review is very important to know the depth of any study. Here the research papers were published between 2016 and 2024, focusing on key areas related to this study. It highlights advancements in facial recognition technologies, particularly the use of Convolutional Neural Networks (CNNs) in various contexts. The review addresses the challenges and methods of indigenous group identification, underscoring the limitations of traditional approaches and the potential of automated systems. It also explores the implications of using technology for cultural preservation, emphasizing the importance of accurate identification in maintaining cultural heritage and promoting social justice. Ethical considerations, such as privacy concerns and potential biases, are discussed, highlighting the need for responsible use of facial recognition technology. This comprehensive analysis provides a solid foundation for the current research, identifying gaps in existing methods and emphasizing the importance of developing an accurate, ethical, and automated system for indigenous group identification.

CHAPTER 3

METHODOLOGY

3.1 Overview

The research subject focuses on utilizing deep learning techniques for the identification of indigenous groups in Bangladesh, specifically targeting the Chakma and Marma communities. The primary objective is to develop robust models capable of accurately identifying individuals belonging to these indigenous groups from facial images. The instrumentation for this research involves the utilization of convolutional neural networks (CNNs), including ResNet50, InceptionV3, Xception, DenseNet121, and VGG16 architectures. These CNN models are chosen for their effectiveness in capturing intricate patterns and features from facial images. Additionally, the dataset used for training and validation purposes comprises 664 facial images, with 328 images representing the Chakma group and 336 images representing the Marma group. Data preprocessing techniques, such as image resizing, enhancement and augmentation are applied to enhance the quality and diversity of the dataset. The integration of these advanced deep learning models aims to advance the field of indigenous group identification, offering a more accurate and efficient approach to recognizing and preserving the cultural heritage of Bangladesh's indigenous communities.

3.2 Proposed Methodology

The methodology for this study involves a systematic approach to identifying Chakma and Marma indigenous groups using deep learning techniques. Initially, facial images of these groups are collected through a combination of field visits in Chittagong and online surveys targeting indigenous students from various universities. Following data collection, preprocessing steps such as resizing, enhancement, and augmentation are applied to create a diverse and balanced dataset. Subsequently, suitable deep learning architectures, including ResNet50, InceptionV3, Xception, DenseNet121, and VGG16, are selected for model training and evaluation. Through transfer learning and optimization techniques, these models are trained on the augmented dataset to enhance their performance. Validation is conducted using a separate validation set to assess the accuracy and generalization capabilities of the trained models. Finally, the validated models undergo testing on an independent test set to measure their effectiveness in accurately identifying Chakma and Marma individuals. Throughout the research process, ethical considerations, such as obtaining informed consent and safeguarding data privacy, are meticulously adhered to, ensuring the ethical integrity of the study. Through this comprehensive methodology, the study aims to develop a robust deep learning approach for indigenous group identification while upholding ethical standards and considerations.

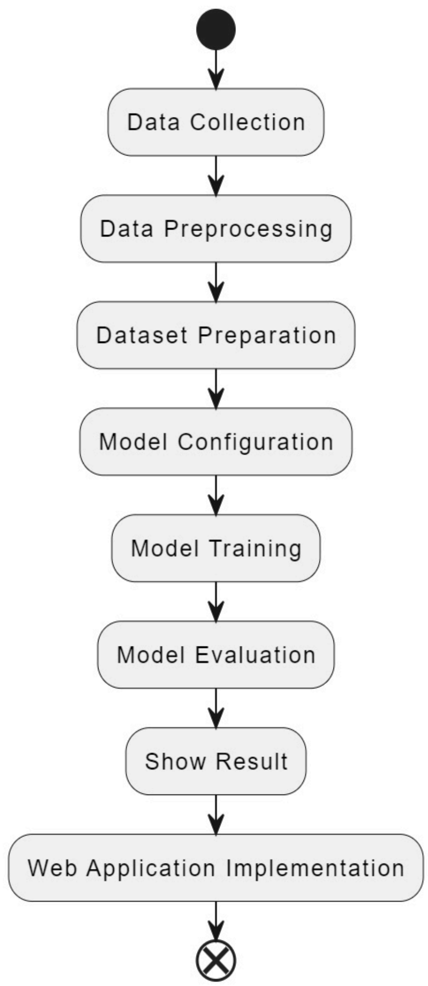

Figure 3.1: Methodology Diagram

Data Collection

A unique dataset of 171 facial image entries were gathered from individual sources, ensuring equitable representation for the ethnic groups Chakma (চাকমা) and Marma (মারমা)

Data Pre-Processing

The data processing pipeline begins with the collection of facial images from various sources, including field visits in Chittagong and online surveys targeting indigenous students from selected universities. Once collected, the images undergo a series of preprocessing steps to ensure consistency and quality in the dataset.

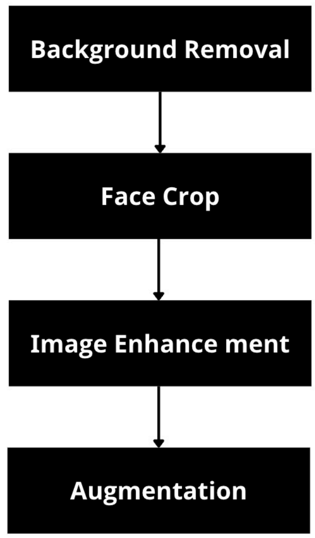

Figure 3.2: Data Preprocessing Step

Background Remove :

The first step in preprocessing involves removing the background from the images to isolate the facial features of the individuals. This helps eliminate any distractions or unnecessary elements that may interfere with the subsequent analysis.

Figure 3.3: Image after background removal

Face Crop:

After background removal, the facial images are passed through a face detection algorithm known as MTCNN (Multi-Task Cascaded Convolutional Neural Network). MTCNN is particularly effective in accurately detecting and localizing faces within images, even in challenging conditions such as varying poses and lighting conditions.

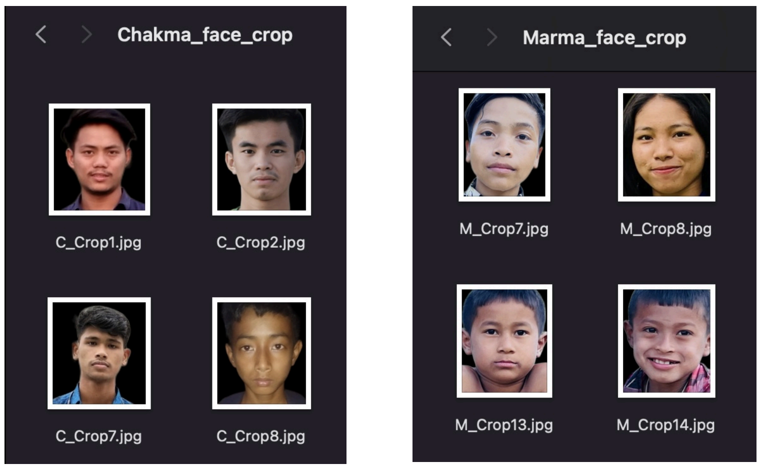

Figure 3.4: Image after Face Crop

Image Enhancement:

Once the faces are successfully detected and cropped, the next step involves image enhancement using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. CLAHE is a powerful method for enhancing the contrast and details in images, particularly in regions with varying illumination. By applying CLAHE to the cropped facial images, we aim to standardize the brightness and contrast levels across the dataset, improving the overall quality and uniformity of the images.

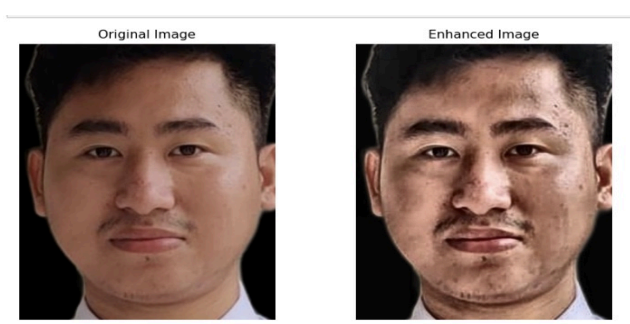

Figure 3.5: Image after background removal

Following image enhancement, data augmentation techniques are applied to further enrich the dataset and improve the robustness of the model. Augmentation involves generating new synthetic images by applying a variety of transformations to the existing images. In this case, four different augmentation dimensions are employed: horizontal flip, rotation, brightness adjustment, contrast adjustment, and noise injection. These transformations help introduce variability and diversity into the dataset, making the model more resilient to variations in pose, lighting, and other factors.

By meticulously performing these preprocessing steps, we ensure that the dataset is well-prepared and optimized for subsequent analysis and model training. The standardized and augmented dataset enhances the effectiveness and generalization capabilities of the deep learning models employed for indigenous group identification.

Model Selection: The Resnet50, VGG16, Densenet121, Xception and InceptionV3 architectures were selected due to their ability to effectively extract sequential information and patterns from the image.

Basic Structure

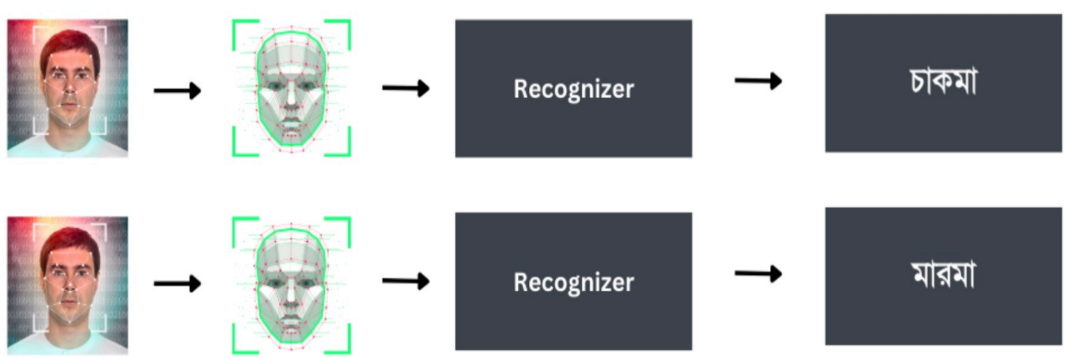

Figure 3.6: Basic Structure

Here are the basic concepts of my used model architecture.

Resnet50

This is the architecture of ResNet50 Model Architecture given below.

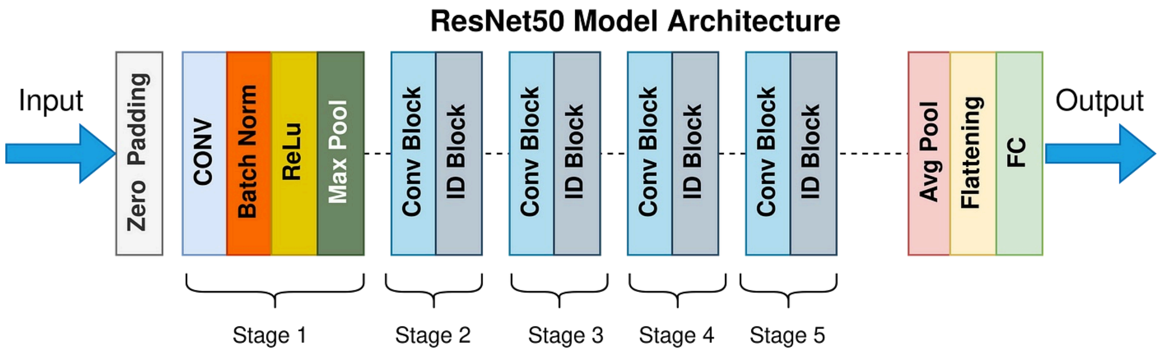

Figure 3.7: Resnet50 architecture

ResNet-50, or Residual Network with 50 layers, is a pivotal convolutional neural network (CNN) architecture introduced by Kaiming He and colleagues in 2015. It addresses the degradation problem, where adding more layers to a neural network leads to higher training error instead of improved performance. ResNet-50's key innovation is the use of residual learning through residual blocks. These blocks consist of convolutional layers, batch normalization, and ReLU activation functions, with shortcut connections that bypass one or more layers. These skip connections allow the network to learn identity mappings, facilitating easier optimization and smoother gradient flow during training. The architecture includes 50 layers, organized into five stages, each with an increasing number of filters and varying numbers of residual blocks. It starts with an initial convolutional layer and a max-pooling layer, followed by the residual blocks, and concludes with a global average pooling layer, a fully connected layer, and a softmax activation function for classification.

VGG16

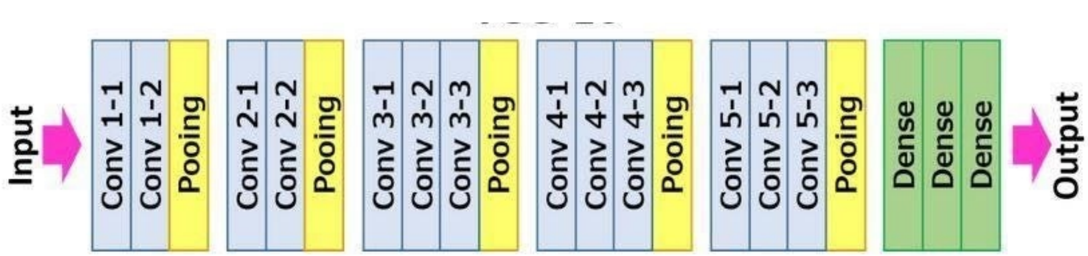

Figure 3.8: VGG16 architecture

VGG16 consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. The architecture follows a simple pattern of stacking convolutional layers with small receptive fields (3x3 filters) and using max-pooling layers to progressively reduce the spatial dimensions of the feature maps. This consistent use of 3x3 filters allows the network to capture complex patterns and details in images while keeping the number of parameters manageable. The model starts with input images of a fixed size, typically 224x224 pixels. It then applies a series of convolutional layers, each followed by a ReLU activation function, to introduce non-linearity. After every few convolutional layers, a max-pooling layer with a 2x2 filter and stride of 2 is used to down-sample the feature maps, effectively reducing the spatial resolution and computational load. The final part of the VGG16 architecture consists of three fully connected layers, each with 4096 neurons, followed by a softmax layer that produces the classification output. This fully connected segment is responsible for making high-level decisions based on the features extracted by the convolutional layers.

DenseNet

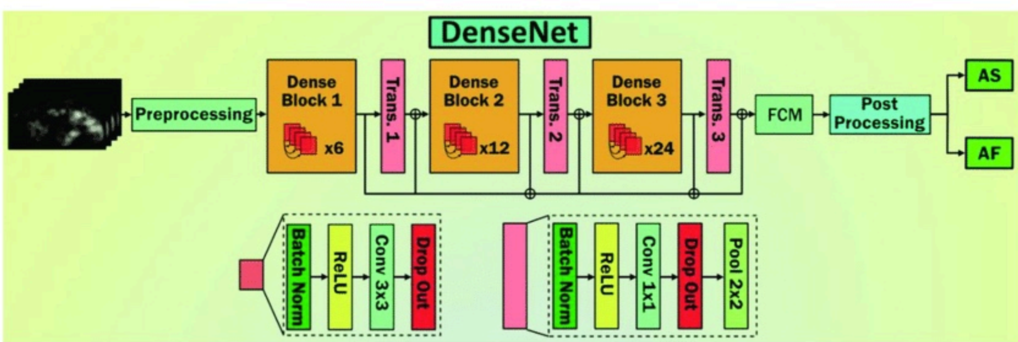

Figure 3.9: DenseNet architecture

Unlike traditional CNNs, DenseNet connects each layer to every other layer in a feed-forward fashion, ensuring maximum information flow between layers. This approach addresses the vanishing gradient problem, improves parameter efficiency, and enhances feature reuse. Each layer receives inputs from all preceding layers and passes its output to all subsequent layers, fostering deeper networks without redundancy.

InceptionV3

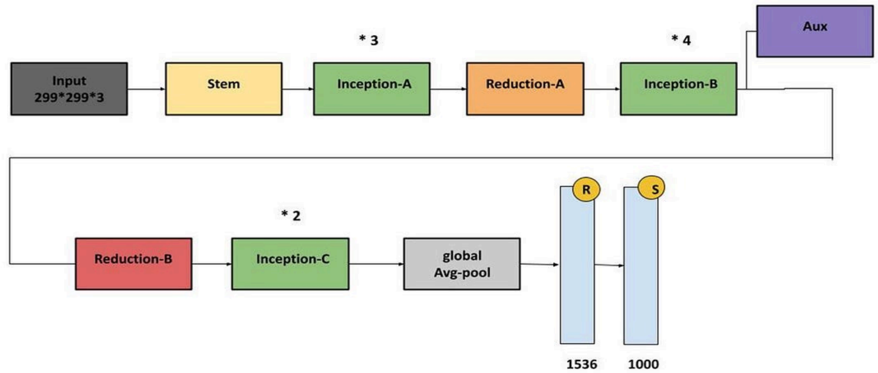

Figure 3.10: InceptionV3 architecture

InceptionV3 employs a unique approach that involves using multiple types of convolutional filters within each module, allowing the network to capture different types of features at various scales simultaneously. This architecture includes several improvements over its predecessors, such as factorized convolutions, efficient grid size reduction, and the use of batch normalization, which help in reducing computational cost while maintaining high accuracy. InceptionV3's modular design and optimized structure make it a powerful and versatile tool for a wide range of computer vision applications.

Xception

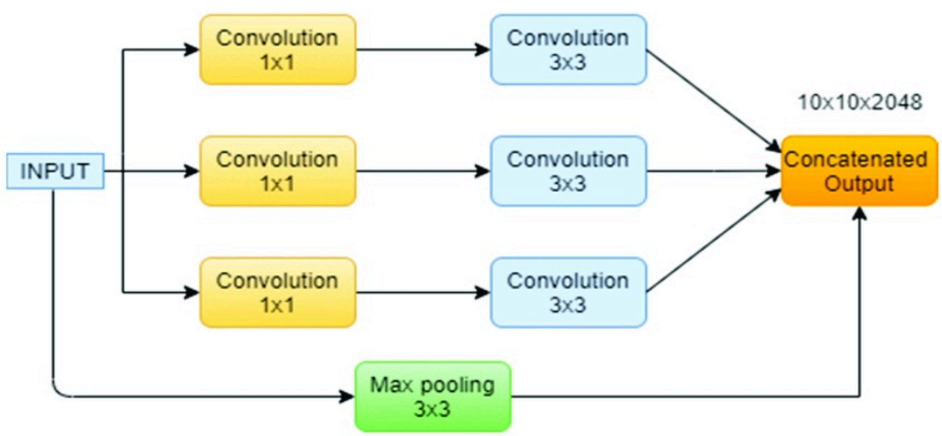

Figure 3.11: Xception architecture

Xception, or Extreme Inception, enhances this concept by replacing standard convolutions with depth wise separable convolutions, which improves efficiency and performance. It builds upon the Inception architecture by replacing the standard Inception modules with depthwise separable convolutions. This change allows the network to capture spatial features more efficiently by first performing a depthwise convolution, which applies a single filter to each input channel, followed by a pointwise convolution, which applies a 1x1 filter to combine the outputs of the depthwise convolution. The Xception architecture consists of 36 convolutional layers structured into 14 modules, each with linear residual connections. This design enhances the model's efficiency and performance by significantly reducing the number of parameters and computational complexity. Xception has demonstrated superior performance on various image classification tasks, making it a highly effective and streamlined architecture for computer vision applications.

Data Collection Procedure

The data collection procedure for this study involved a combination of manual fieldwork and online surveys to gather facial images of the Chakma and Marma indigenous groups. Given that indigenous communities are primarily located in Chittagong, extensive field visits were conducted in the region to manually collect facial data. Additionally, to ensure a diverse dataset, a Google Form was created to collect data from indigenous group students attending various universities, notably Chittagong University of Engineering and Technology, Chittagong University, Jahangirnagar University, and Daffodil International University. This approach aimed to broaden the scope of the dataset and capture a representative sample of indigenous individuals. However, the data collection process posed significant challenges due to the sensitive nature of capturing facial images and the need for informed consent. Despite these hurdles, diligent efforts were made to gather a comprehensive dataset encompassing both Chakma and Marma groups for classification purposes. So the group/ class of my dataset are -

- Chakma
- Marma

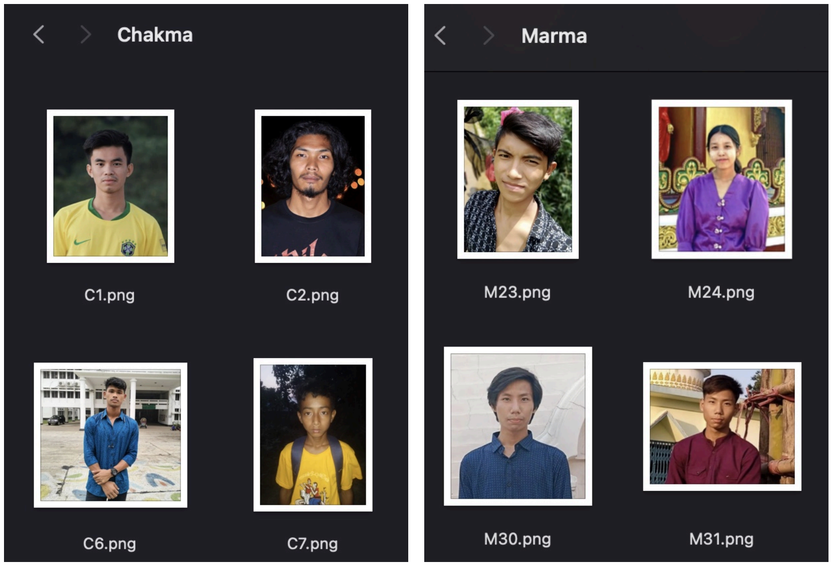

Figure. 3.12: Photos of Chakma and Marma

Statistical Analysis

These statistics provide insights into the distribution and allocation of data within my dataset, including the original raw data, augmented data, and how they are split across different subsets for training, validation, and testing purposes.

Total Number of Raw Data

Chakma: 86 Photos and Marma: 85 Photos

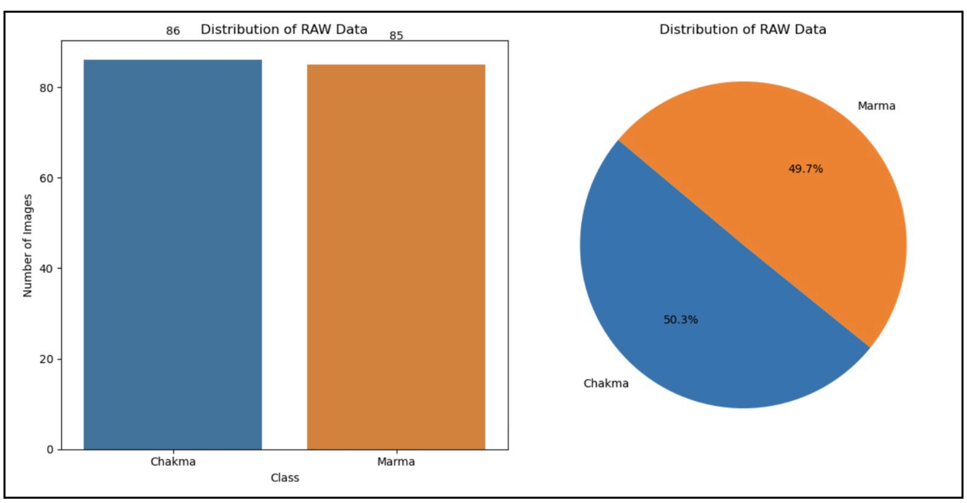

Figure 3.13: Bar Chart and Pie Chart for RAW data

Table. 3.1: Distribution of data

Raw Data	Augmented Data	Training Set	Validation Set	Test Set
Chakma : 86 Marma : 85	Chakma : 329 Marma : 337	Chakma : 263 Marma : 268	Chakma : 30 Marma : 34	Chakma :35 Marma :35
Total : 171	**Total : 666**	**Total : 531**	**Total : 64**	**Total :70**

So, RAW data is of 171 facial images and after augmentation my total data is 666 in two different groups. And for training, validation and testing I splitted the data by using code automation. Where 80% is taken for training and 10% is taken in validation and 10% in testing. Data splitting is very important in training and evaluating the model properly. Data splitting involves dividing the prepared dataset into distinct subsets for training, validation, and testing purposes. The training set is used to train the deep learning models, the validation set is employed to fine-tune model hyperparameters and monitor performance, while the test set is reserved for evaluating the final model's performance on unseen data. This ensures an unbiased assessment of the model's generalization capabilities.

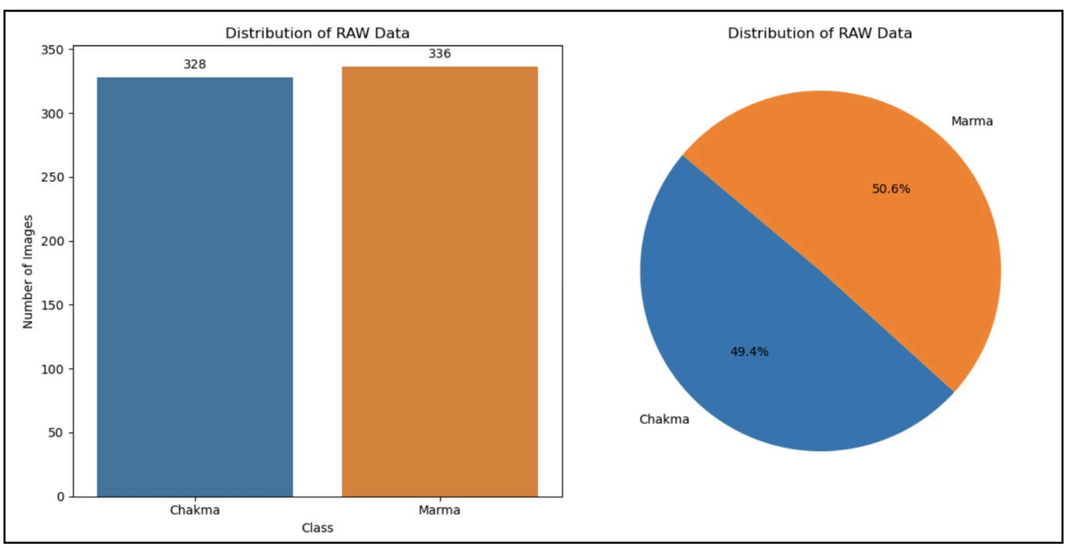

Figure 3.14: Bar Chart and Pie Chart for augmented data

3.3 Hardware/ Software Requirement

The implementation requirements for this work involve several key components essential for the successful execution of the project. Firstly, a robust computational infrastructure is necessary to support the training and evaluation of deep learning models. This includes access to high-performance GPUs or TPUs to expedite the processing of large image datasets. Additionally, software tools such as TensorFlow, Keras, or PyTorch are required for implementing and fine-tuning convolutional neural network architectures like ResNet50, InceptionV3, Xception, DenseNet121, and VGG16. Besides, a reliable programming environment, preferably Python, is indispensable for coding and scripting tasks related to data preprocessing, model training, and performance evaluation. Additionally, access to specialized libraries for image processing and manipulation, such as OpenCV is essential for handling facial images effectively. Large storage space is necessary to accommodate the extensive dataset comprising facial images of the Chakma and Marma indigenous groups. This requires local storage solutions. Besides, a suitable development environment for web application deployment is required if the research involves creating a user interface or web-based platform for model deployment and interaction.

3.4 Project Management and Financial Analysis

The management of the project is done independently, which simplifies the management process significantly. Utilizing available resources for model training and development has enabled smooth progress without encountering major financial constraints thus far. With sole responsibility for the project's execution, project management has been straightforward and manageable.

Managing the process of capturing facial images was a crucial aspect of the project, particularly considering the diverse locations and communities involved. Coordinating with individuals to capture photos posed certain challenges, as not everyone was familiar with the research objectives or comfortable with having their photos taken. However, considering future prospects, the project may encounter complexities and increased costs, particularly if adaptation for various devices becomes necessary. Potential modifications for device-specific compatibility could entail additional resources and funding requirements.

Finance: The process of collecting the dataset involved visiting different regions of Chittagong, Bangladesh, where indigenous communities primarily reside. This endeavor demanded logistical planning and incurred expenses related to travel, accommodation, and data acquisition. Such fieldwork enriched the dataset with diverse samples, crucial for robust model training and validation.

Project Management Time Period

Data set collection was the most crucial part of this work. So 3 months have been invested to collect good quality of data across the different areas of Chittagong. Besides, different approaches were taken, like google forms and people engagement in different places. So, 3 months was necessary for the dataset.

Table 3.2: Project Management Table

WORK	TIME
Dataset Preparation	3 Months
Literature Review	2 Months
Environment Setup	1 Month
Implementation	2 Months
Report	2 Months
Total	**10 Months**

3.5 Summary

The research methodology for this thesis involves several critical phases designed to develop and evaluate a deep learning model for identifying Chakma and Marma individuals from facial images. Initially, a comprehensive dataset of 664 facial images (328 Chakma and 336 Marma) was collected and preprocessed, including resizing, normalization, and augmentation to enhance the diversity and robustness of the data. Following this, various Convolutional Neural Network (CNN) architectures—ResNet50, VGG16, InceptionV3, and DenseNet121—were selected for training. The models were fine-tuned using techniques such as cross-validation and regularization to optimize performance. Ethical considerations, including privacy and bias mitigation, were integral to the methodology to ensure responsible and fair use of the technology.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

The implementation phase involves setting up the infrastructure necessary for training and evaluating Convolutional Neural Network (CNN) models, including data preprocessing of 664 facial images (328 Chakma and 336 Marma), resizing, normalizing, and augmenting the images, and configuring the computational environment. During the model training phase, CNN architectures such as ResNet50, VGG16, InceptionV3, and DenseNet121 are fine-tuned for optimal performance in identifying Chakma and Marma individuals, utilizing techniques like cross-validation and regularization to prevent overfitting. Performance metrics such as accuracy, precision, recall, and F1-score are employed to evaluate the models. The system testing phase rigorously evaluates the trained models on a separate test set to assess real-world performance, robustness under varying conditions, and overall reliability, efficiency, and scalability. Ethical considerations, including privacy and bias mitigation, are reviewed to ensure the system's responsible and fair use, resulting in a technically sound and culturally sensitive tool for identifying indigenous groups in Bangladesh.

4.2 Train Model

Model training is at the core of this work, utilizing convolutional neural networks (CNNs) to identify the Chakma and Marma indigenous groups in Bangladesh. This training process highlights the efficacy of deep learning techniques.The trained models provide valuable tools for accurately recognizing and preserving the rich diversity of Bangladesh's indigenous communities. The evaluation process involved testing the trained models on unseen data to measure their accuracy, precision, and recall. By comparing the predicted labels with the ground truth, we assessed each model's ability to correctly classify Chakma and Marma individuals. Additionally, metrics such as confusion matrices and receiver operating characteristic (ROC) curves were utilized to provide a comprehensive understanding of model performance. To check the work accuracy and how it is performing testing is very important. This test serves as the final check of the convolutional neural networks (CNNs) trained in this work for identifying the Chakma and Marma indigenous groups in Bangladesh. Performing training and validation, the test model evaluates the performance of the trained CNN architectures, including ResNet50, VGG16, InceptionV3, Xception and DenseNet121, on previously unseen data. During the testing phase, the trained models are presented with a separate set of facial images not encountered during training or validation. These images represent real-world scenarios and are crucial for assessing the models' ability to generalize to new and unseen data. By comparing the model's predictions with the ground truth labels, the test model determines the accuracy, precision, recall, and other performance metrics of each CNN architecture.

4.3 Model Evaluation

Here is our system implementation. Where we are able to upload a photo of a specific indigenous group and our model can determine whether it is “Chakma” or “Marma” with confidence. Besides It can detect whether a face is found or not. If there is face detected then the model will run for identification.

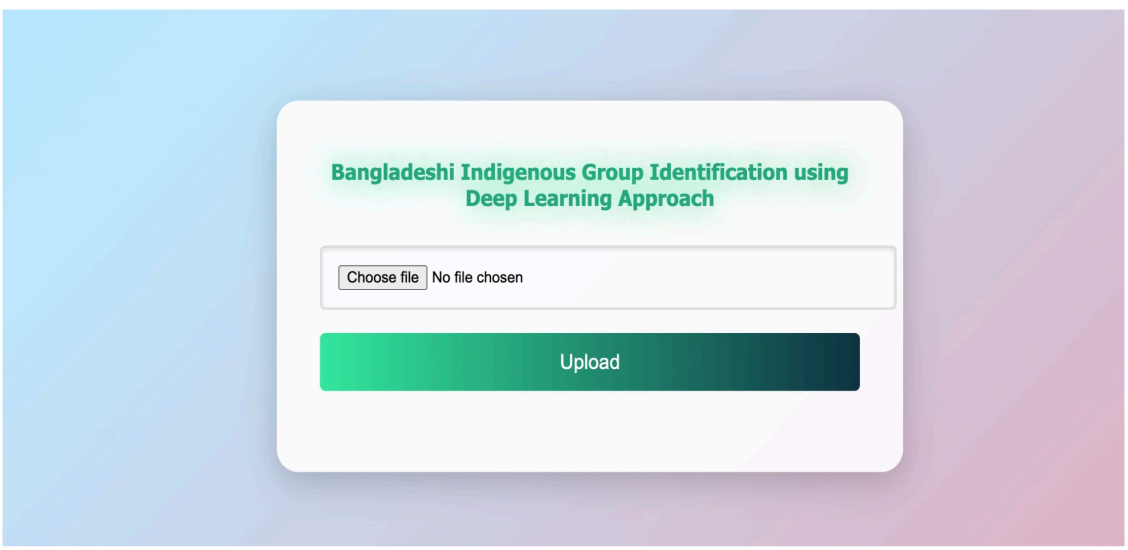

Figure 4.1: Web Implementation

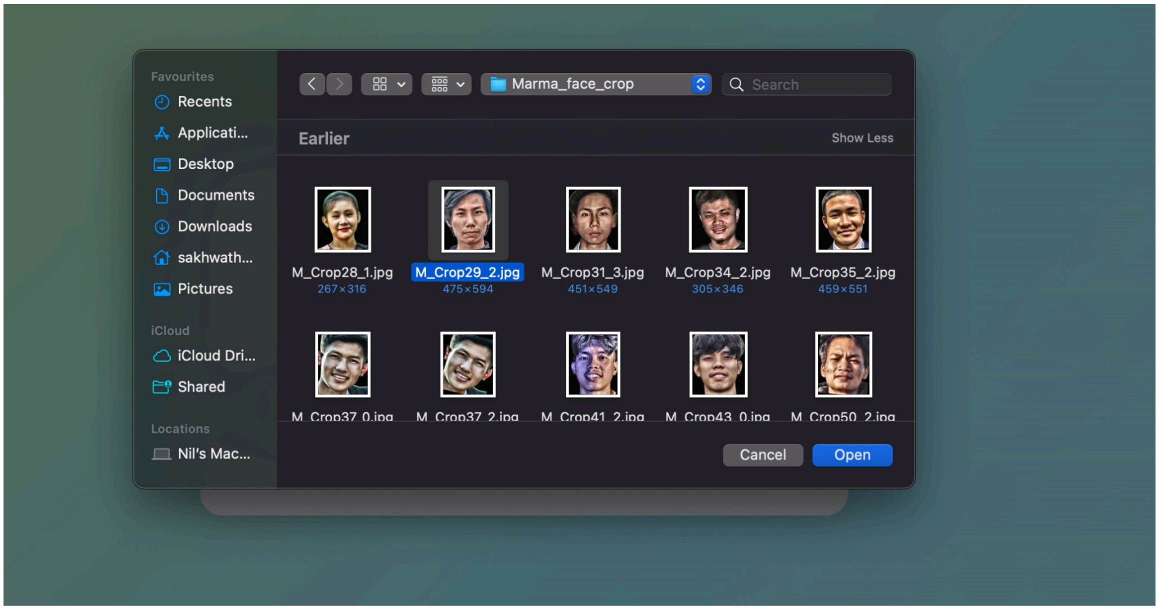

Figure 4.2: Web Implementation : Choosing Photo

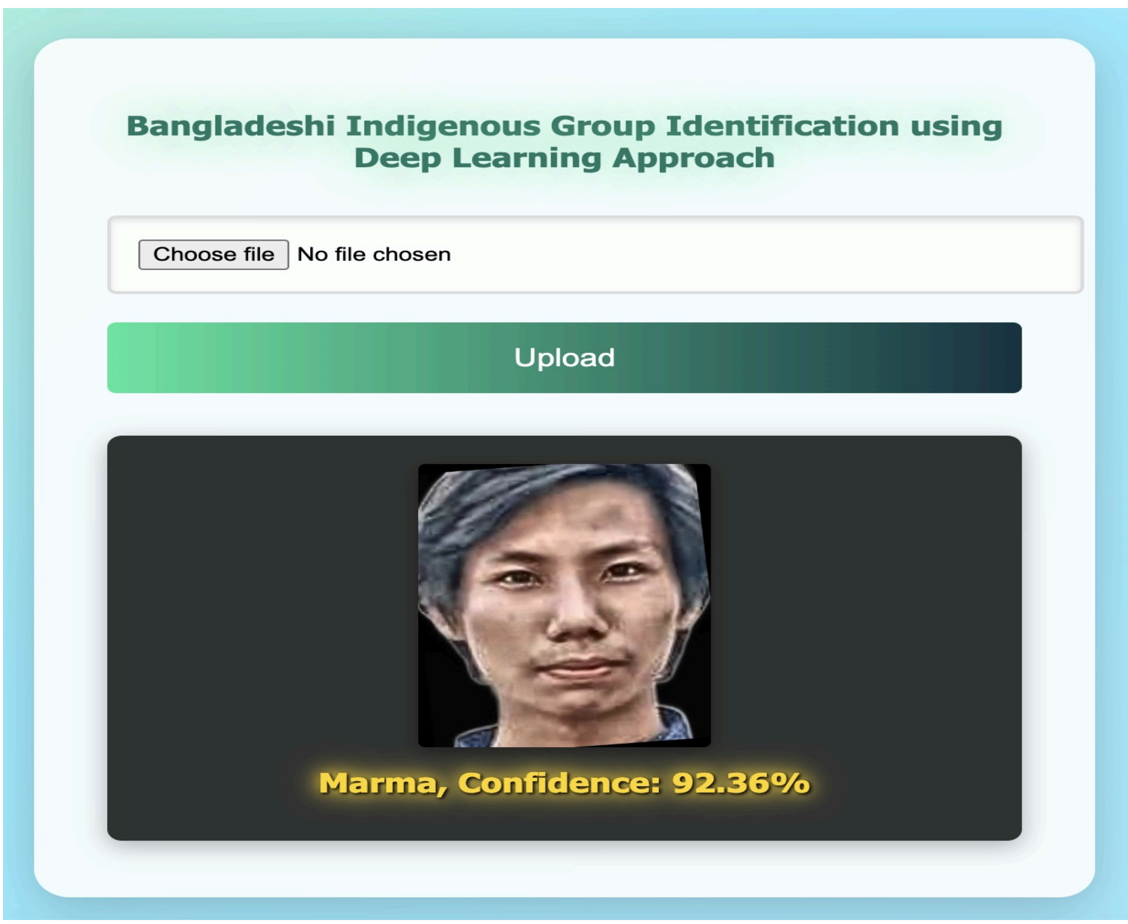

Figure 4.3: Web Implementation - Predicted Class

4.4 Summary

The implementation phase focuses on establishing the necessary infrastructure for training and evaluating Convolutional Neural Network (CNN) models. This involves preprocessing a dataset of 664 facial images (328 Chakma and 336 Marma) by resizing, normalizing, and augmenting the images to enhance diversity and model robustness. Additionally, the computational environment is configured to ensure all required libraries and frameworks for deep learning are installed and properly set up. This phase sets the groundwork for the subsequent stages of model training and system testing, ensuring that the data is well-prepared and the environment is ready for rigorous experimentation and evaluation.

CHAPTER 5

RESULTS AND ANALYSIS

5.1 Overview

This section of the work presents the findings from the implementation and evaluation of various Convolutional Neural Network (CNN) models—ResNet50, VGG16, InceptionV3, and DenseNet121—used to identify Chakma and Marma individuals from facial images. The performance of each model is assessed using metrics such as accuracy, precision, recall, and F1-score. Comparative analysis highlights the strengths and weaknesses of each model, providing insights into their effectiveness and suitability for this specific application. The analysis also discusses the impact of data augmentation, preprocessing techniques, and hyperparameter tuning on the models' performance. Additionally, the section explores the ethical considerations, including bias and fairness, ensuring that the developed system adheres to ethical standards while accurately identifying indigenous groups. The comprehensive analysis aims to validate the models' reliability and robustness in real-world scenarios, emphasizing the potential of deep learning in addressing complex societal challenges.

5.2 Experimental Results

This experiment trained and tested several convolutional neural network (CNN) models, including ResNet50, VGG16, InceptionV3, Xception and DenseNet121, on a dataset of 664 facial images. This dataset consisted of 328 images from the Chakma group and 336 from the Marma group. We evaluated the models based on training accuracy and test accuracy.

ResNet50 was the top performer with a Training Accuracy of 95.85% and a Test Accuracy of 95.52%. It showed excellent ability to distinguish between Chakma and Marma individuals, proving its robustness with the dataset.

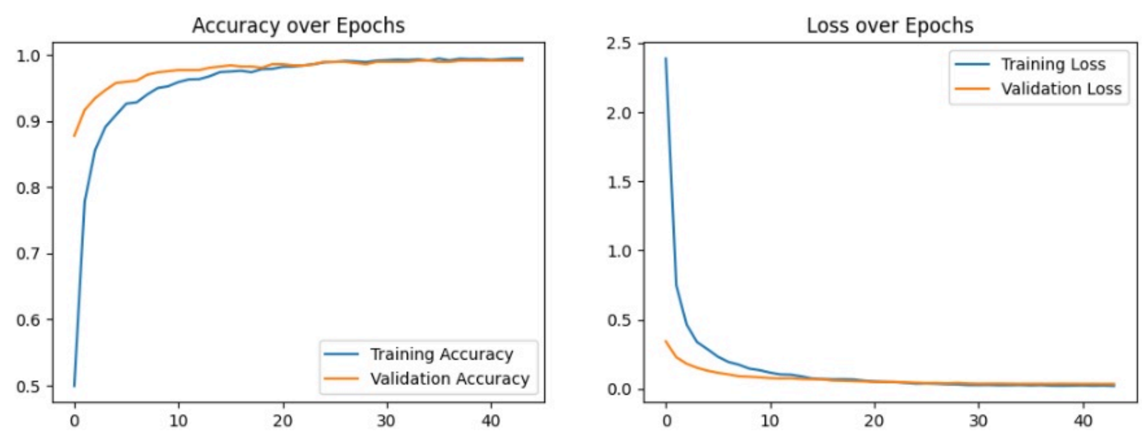

Figure 5.1: Model accuracy and loss (Resnet50)

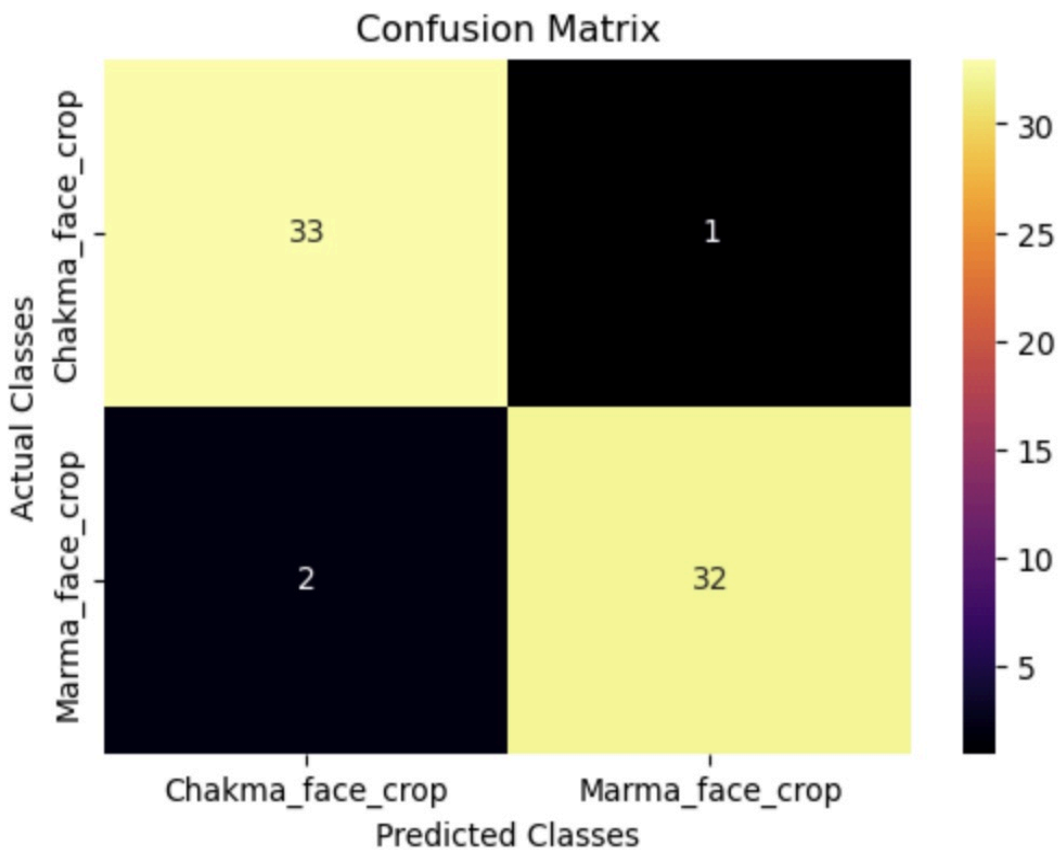

Figure 5.2: Confusion Matrix for Resnet50

VGG16 achieved a Training Accuracy of 94.34% and a Test Accuracy of 88.06%. While slightly lower than ResNet50, it still performed highly in the classification task in the training set.

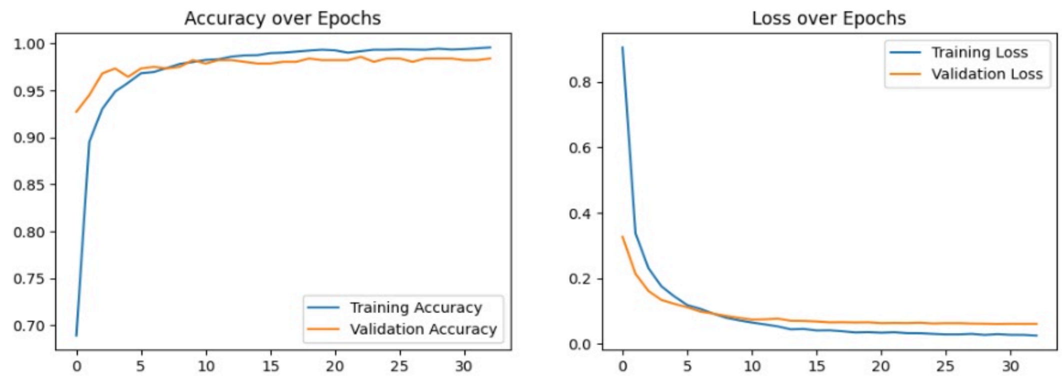

Figure 5.3: Model accuracy and loss (VGG16)

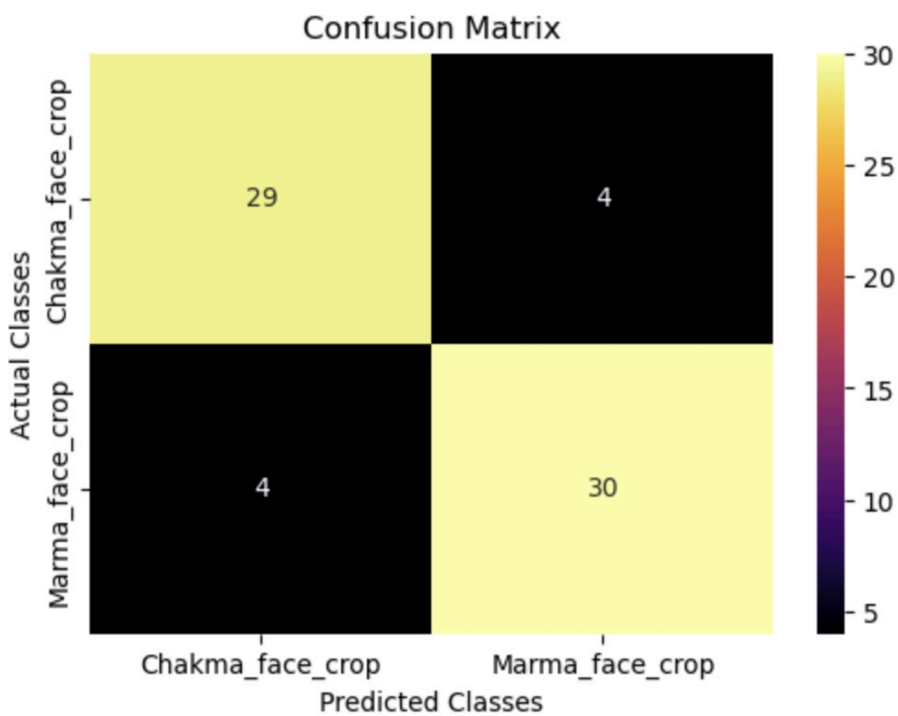

Figure 5.4: Confusion matrix for VGG16

InceptionV3 recorded a Training Accuracy of 97.92% and a Test Accuracy of 86.57%, showing good performance in training but less precision in test compared to ResNet50 and VGG16.

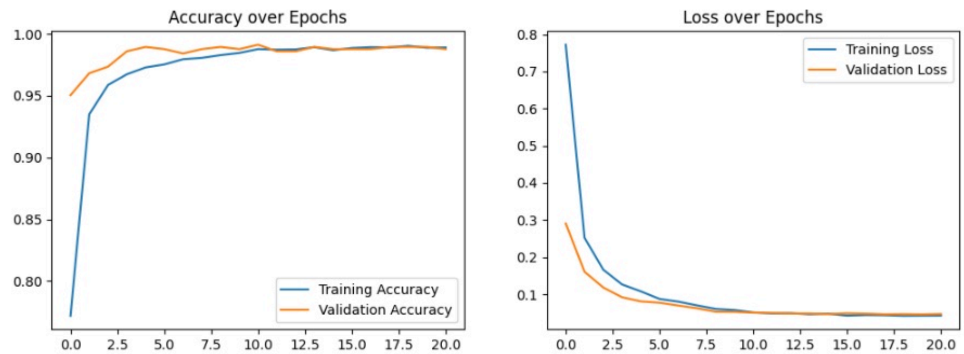

Figure 5.5: Model accuracy and loss (InceptionV3)

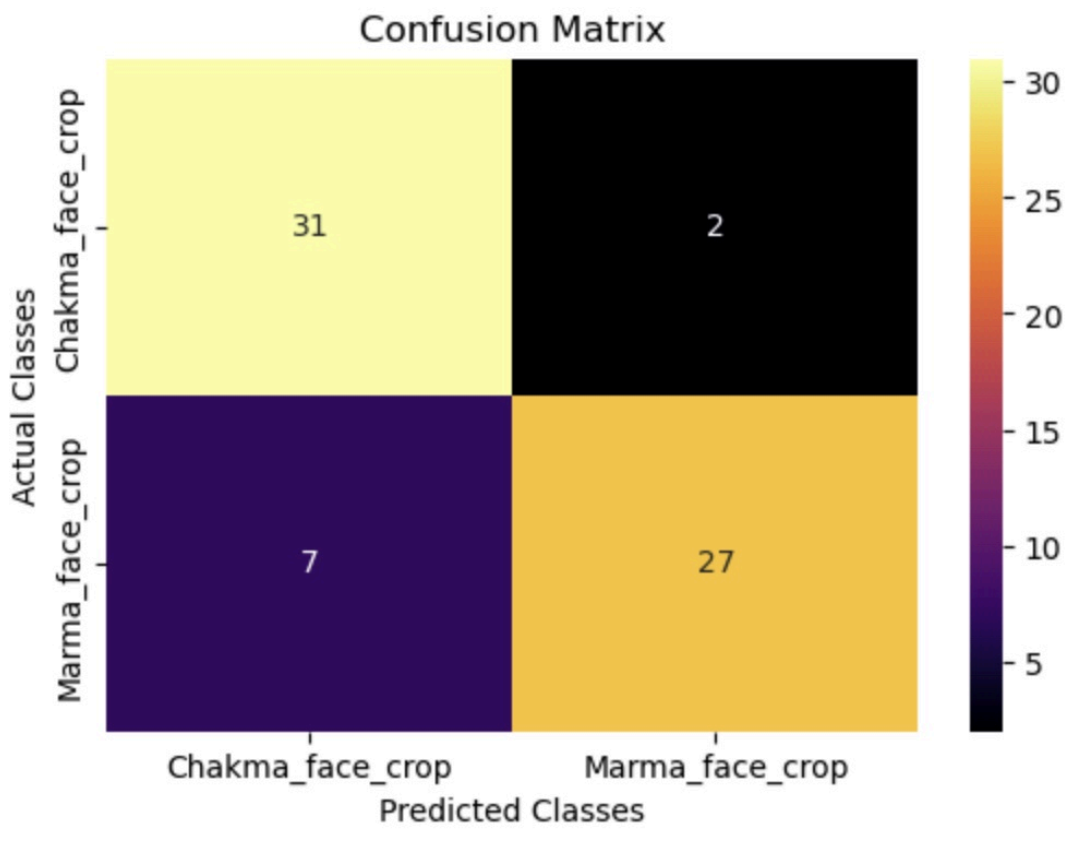

Figure 5.6: Confusion matrix for InceptionV3

DenseNet121 had a Training Accuracy of 89.62% and a Test Accuracy of 91.04%, indicating good performance but not as effective as ResNet50.

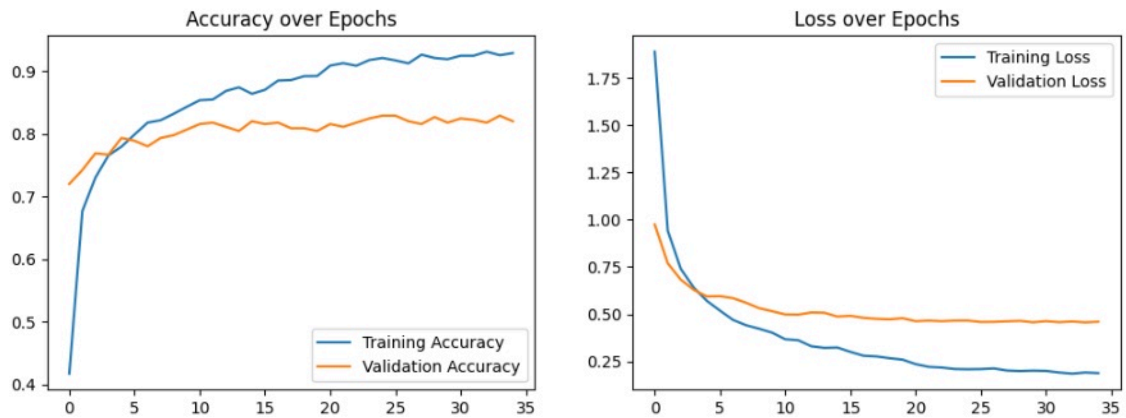

Figure 5.7: Model accuracy and loss (DenseNet121)

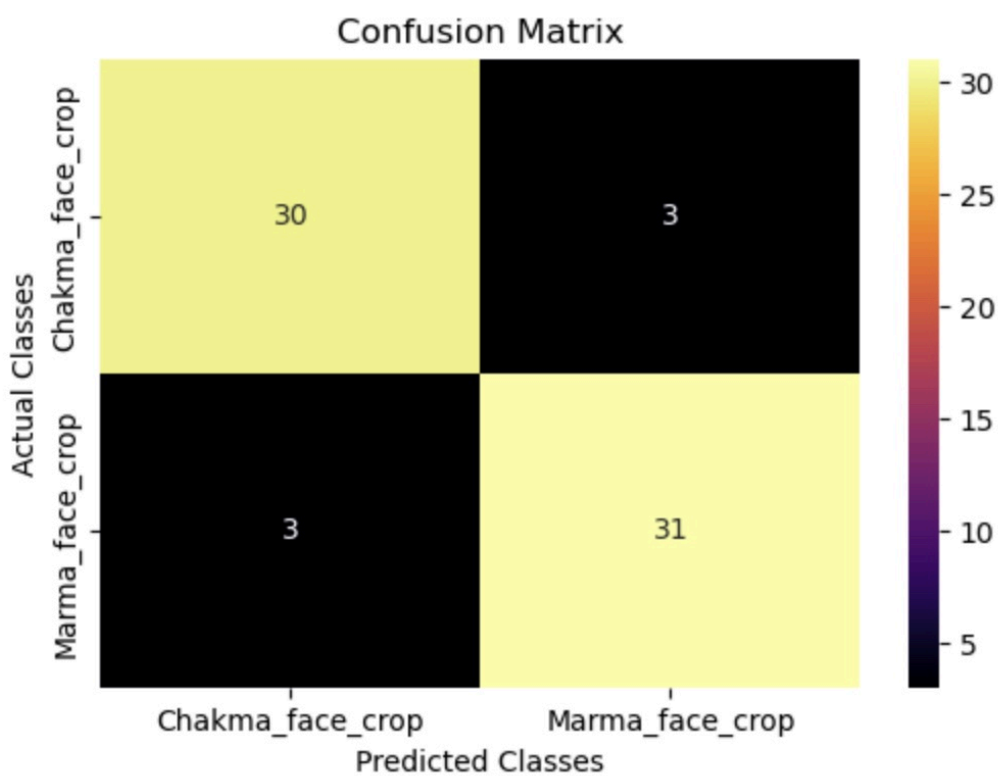

Figure 5.8: Confusion Matrix for DenseNet121

Xception got a Training Accuracy of 91.70% and a Test Accuracy of 91.18%, similar to Inceptionv3 but lower than ResNet50 and DenseNet121.

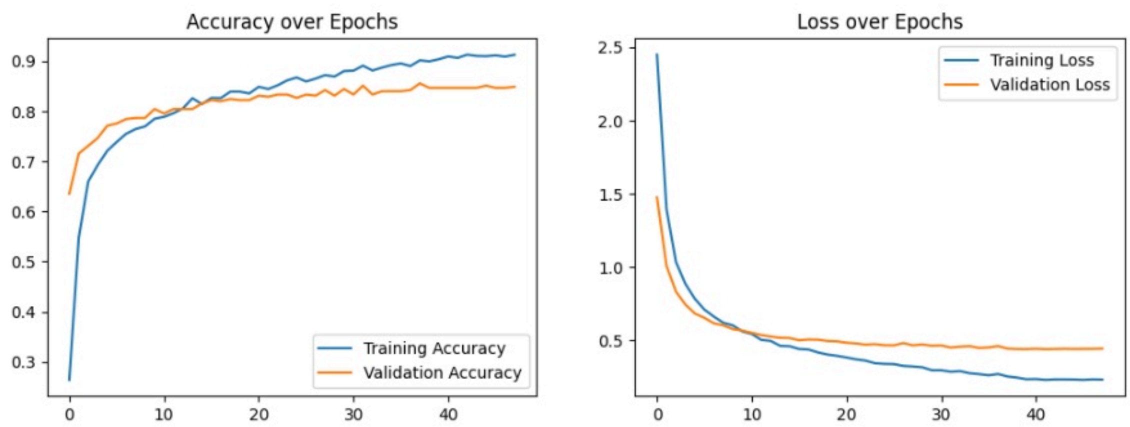

Figure 5.9: Model accuracy and loss (Xception)

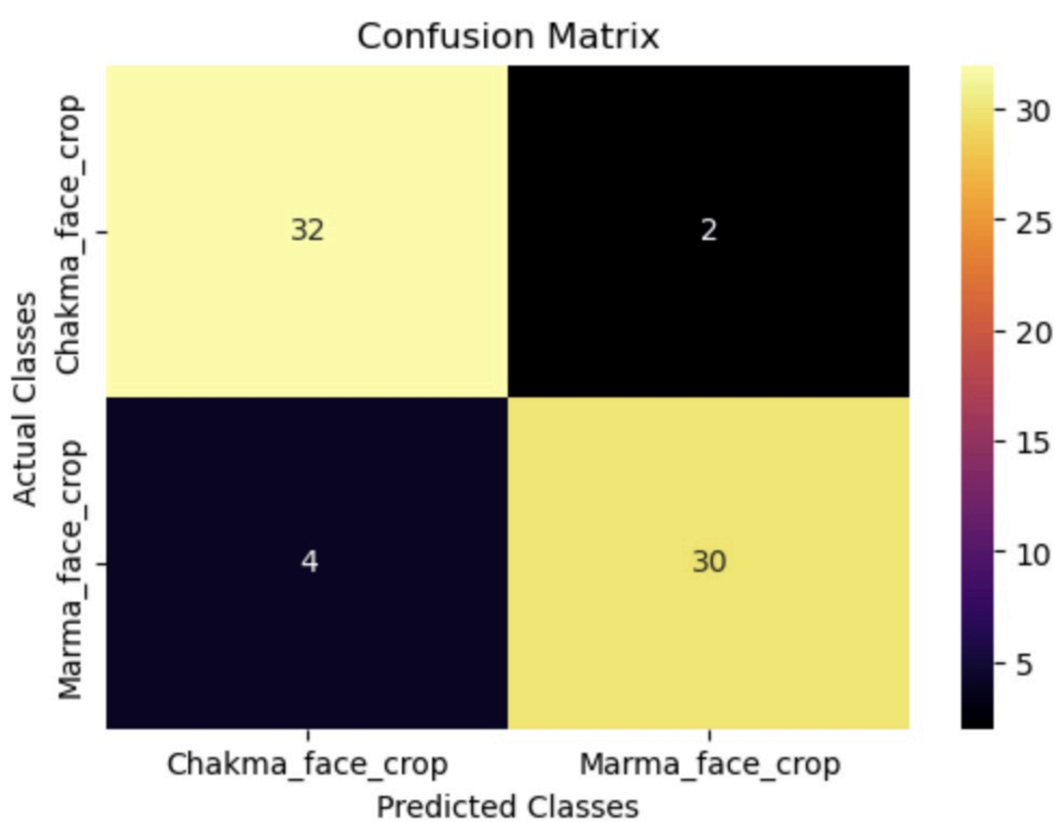

Figure 5.10: Confusion Matrix for Xception

5.3 Comparative Analysis

The models, especially ResNet50, showed high accuracy in identifying individuals from the Chakma and Marma groups, with ResNet50 achieving a training accuracy of 95.85% and a test accuracy of 95.52%. These results highlight the potential of deep learning techniques in accurately recognizing indigenous groups, which can be useful for applications such as cultural preservation, social justice advocacy, and customized healthcare services. The study acknowledges challenges, such as the diversity within the facial features of the indigenous groups and the need for a diverse and representative dataset. Ethical considerations are emphasized, ensuring the technology respects the privacy and cultural sensitivities of the communities involved. The discussion also highlights the broader societal implications, suggesting that these models can promote inclusivity, equity, and mutual respect in society. Future research directions include expanding the dataset to include more indigenous groups, addressing potential biases, and exploring the impact of different dataset sizes and features on model performance. Additionally, the study suggests the need for continuous monitoring and transparent communication of model performance to maintain trust and accountability.

Table. 5.1: Accuracy Comparison

Model Name	Training Accuracy	Test Accuracy
ResNet50	95.85	95.52
DenseNet121	89.62	91.04%
VGG16	94.34%	88.06%
InceptionV3	97.92%	86.57%
Xception	91.70%	91.18%

5.4 Summary

The analysis of the experimental results reveals several key points. ResNet50's superior performance is due to its deeper architecture and the use of residual connections, which help prevent the vanishing gradient problem and improve feature extraction from facial images. Although relatively small, the dataset was balanced between the two groups, aiding in effective model training without significant bias. Data augmentation techniques, such as image rotation, flipping, and scaling, increased the diversity of the training data, contributing to the robust performance of the models. The training process included careful monitoring of loss and accuracy metrics to avoid overfitting. Cross-validation techniques ensured that the models generalized well to unseen data, as shown by the consistent test accuracies. While VGG16, InceptionV3, and DenseNet121 performed well, ResNet50's architecture provided a clear advantage in capturing detailed patterns in the facial features specific to the Chakma and Marma groups. This suggests that deeper networks with residual connections might be more effective for similar tasks involving detailed image classification. We acknowledged the potential for bias in the dataset and the models. Efforts were made to ensure fair representation of both indigenous groups in the dataset. However, further studies with larger and more diverse datasets could help in understanding and mitigating any remaining biases.

In conclusion, the experimental results and analysis highlight the effectiveness of deep learning, particularly the ResNet50 model, in identifying Bangladeshi indigenous groups. This research advances the technical understanding of CNNs in facial recognition tasks and has significant implications for preserving cultural heritage and promoting social justice. The findings pave the way for further research and development, aiming for even higher accuracy and broader applications.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The implementation of deep learning for the identification of indigenous groups, specifically the Chakma and Marma communities in Bangladesh, has profound implications for their daily lives and societal integration. This technology enhances the recognition and preservation of their cultural identities, facilitating greater appreciation and respect for their unique traditions, languages, and ways of life. By providing an accurate and automated identification system, it reduces the burden of laborious and biased traditional methods, ensuring fairer and more reliable recognition of these communities. Moreover, this advancement promotes social justice by enabling more equitable access to resources and opportunities. Accurate identification can improve access to government services, educational opportunities, and healthcare tailored to the specific needs of these communities. So, the impact of this thesis on life extends beyond technological innovation to enhancing cultural preservation, promoting social justice, and ensuring ethical considerations are upheld, ultimately contributing to a more inclusive and respectful society.

6.2 Impact on Society and Environment

The successful development of accurate indigenous group identification models using deep learning techniques holds significant implications for societal harmony and inclusivity. By enabling the automatic recognition of indigenous identities from facial images, these models have the potential to foster cross-cultural understanding, promote tolerance, and mitigate social impacts stemming from marginalization and discrimination. Applications of such technology extend beyond academic research and technical innovation to encompass practical societal benefits. For instance, the implementation of indigenous group identification models could facilitate customized services and resources tailored to the specific needs of Chakma and Marma communities in Bangladesh. This may include targeted healthcare interventions, educational programs, and social services designed to address the unique cultural and linguistic characteristics of these groups.

Furthermore, the utilization of deep learning for indigenous group identification has implications for multicultural marketing and representation. By accurately identifying Chakma and Marma individuals, businesses and organizations can develop culturally sensitive marketing campaigns and products that resonate with these communities, thus fostering economic empowerment and social inclusion. However, it is essential to approach the ethical considerations of such technology with careful consideration and sensitivity. Ensuring justice, transparency, and accountability in the development and deployment of indigenous group identification models is paramount to prevent unintended consequences and safeguard against potential biases. The societal impact of deep learning-based indigenous group identification lies in its ability to contribute to the creation of a more compassionate, integrated society that celebrates and respects linguistic and cultural diversity. While the environmental impact of developing indigenous group identification models may be overshadowed by their societal benefits, it remains imperative to prioritize sustainability in technological advancements and ensure that innovation aligns with environmental conservation goals.

6.3 Ethical Aspects

The development and deployment of deep learning-based indigenous group identification models necessitate careful attention to ethical considerations throughout the process. To mitigate the risk of perpetuating biases and prejudices, it is imperative to ensure fair representation and minimize biases in the training data. Transparent documentation of data sources, model architecture, and limitations is essential to uphold ethical standards in AI techniques. Moreover, ethical principles should guide the examination of potential societal implications, taking into account cultural sensitivities and privacy concerns specific to indigenous communities. Respecting individual autonomy and informed consent is paramount in data collection and usage, particularly when dealing with sensitive personal information such as facial images. To foster trust and accountability, continuous monitoring of model performance and outcomes, along with transparent communication of findings, is crucial. Community engagement throughout the development and implementation phases ensures that the perspectives and concerns of indigenous communities are considered and addressed. Finding a balance between technological advancements and ethical responsibilities is essential in navigating the ethical complexities inherent in indigenous group identification. This requires ongoing conversations, interdisciplinary collaboration, and the incorporation of diverse perspectives to ensure that the development and deployment of such models align with ethical principles and contribute positively to societal well-being.

6.4 Sustainability Plan

The sustainability plan for the development and implementation of indigenous group identification models using deep learning techniques encompasses resource optimization through energy-efficient hardware and cloud computing, adherence to ethical principles to mitigate biases and ensure transparency, continuous community engagement to address concerns and share benefits equitably, capacity building initiatives to empower local stakeholders, establishment of a robust monitoring and evaluation framework for adaptive management, and knowledge sharing and collaboration with relevant stakeholders to contribute to broader efforts in indigenous rights, AI ethics, and sustainable development.

6.5 Summary

The implementation of deep learning for the identification of indigenous groups, specifically the Chakma and Marma communities in Bangladesh, has significant impacts on society, the environment, and sustainability. This technology enhances the recognition and preservation of cultural identities, promoting social justice and equitable access to resources and opportunities. By providing accurate and automated identification, it reduces bias in traditional methods and fosters inclusivity, leading to better access to services, education, and healthcare for these communities. The environmental impact of computational resources used in deep learning can be mitigated through energy-efficient technologies and practices. A comprehensive sustainability plan includes optimizing resources, adhering to ethical standards, engaging with communities, building local capacities, and establishing monitoring frameworks. This plan ensures that technological advancements contribute positively to societal well-being and align with broader goals of environmental sustainability and cultural preservation.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

This research demonstrates the efficacy of convolutional neural networks (CNNs) in accurately identifying the Chakma and Marma indigenous groups in Bangladesh. Through careful evaluation of various CNN models, ResNet50 emerged as the most effective, achieving impressive accuracy rates. Beyond technical achievements, the research highlights the diverse applications of indigenous group identification, spanning cultural preservation, social justice advocacy, healthcare, product and service recommendation and more. By shedding light on the potential of deep learning in addressing societal challenges, this work contributes to both academic knowledge and practical solutions. The developed web application serves as a valuable tool for recognizing and honoring the rich cultural diversity of Bangladesh's indigenous communities, making development easier for greater inclusivity and understanding in our society.

7.2 Further Suggested Works

This work lays the groundwork for future investigations in indigenous group identification, highlighting the efficacy of deep learning algorithms. There are other indigenous groups in Bangladesh. For example, Garo, Tripura, Manipuri, Munda, Oraon, Santal, Khasi, Kuki, Tripura, Mro, Hajong and Rakhain. We can enrich this model by collecting more data of different groups and achieve better result and better cultural diversity. Subsequent research endeavors should prioritize addressing potential biases, evaluating model generalization across diverse facial structure, and expanding ethical considerations to encompass broader societal impacts. Additionally, exploring the impact of varying dataset sizes and features on model performance could enhance comprehension. Further exploration into explainability techniques is warranted to enhance transparency and foster trust in the developed models. Sustained advancements in ethical frameworks, environmental sustainability, and interdisciplinary collaboration are imperative for the continued ethical and sustainable evolution of automated indigenous group identification systems.

7.3 Limitations

Despite the promising results of this study on Bangladeshi indigenous group identification using deep learning techniques, several limitations must be acknowledged. The dataset used was relatively small and limited to only two indigenous groups, which may affect the model's ability to generalize across diverse populations and conditions. Additionally, while ResNet50 demonstrated strong performance, there was notable variability in model performance, with DenseNet121 showing high training accuracy but lower test accuracy. The study also faces potential biases related to data collection methods and raises ethical concerns around the use of facial recognition technologies, such as issues of consent and privacy. Moreover, the effectiveness of the developed web application in real-world scenarios remains to be thoroughly tested, and the technological constraints of the current computational resources may limit further advancements. Addressing these limitations will be crucial for future research to enhance model robustness, broaden applicability, and ensure ethical deployment of the technology.

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Appendix A

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

Title:
Bangladeshi Indigenous Group Identification using Deep Learning Approach

Student ID: 201-15-13731

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **ethnicity detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like VGG19 and ResNet152v2, enhancing pneumonia detection accuracy in chest X-ray images, crucial for computer-aided diagnosis.	**Page no:** [26-30] **Section:** [3.2] **Page no:** [1-7] **Section:** [1.1]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [30] **Section:** [3.2(B)] **Page no:** [33]

					Section: [3.4]
				This project ensures K8 **(Research Literature)** by synthesizing insights from recent studies, to advance pneumonia detection using deep learning, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-7] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in pneumonia detection, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [23-24] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing pneumonia detection amidst multiple potential approaches.	**Page no:** [36-57] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in respiratory diseases like pneumonia, contributing to advancements in public health and healthcare practices which indicates **EP-4**.	**Page no:** [16-24] **Section:** [2.2, 2.4]

5.	**EP5: Extends of applicati on codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakehold ers involved and conflictin g requirem ents**	No	CO8	N/A	N/A
7.	**EP7: Interdep endence**	Yes	CO5	This project's comprehensive approach addresses high-level problems by integrating various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in ethnicity detection which ensures **EP-7**.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in pneumonia detection through transfer learning and deep CNNs.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving healthcare through advanced pneumonia detection methods, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [58-61] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in pneumonia detection through transfer learning and deep CNNs, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [7-10] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [13] **Section:** [1.6]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing people privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [60] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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