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Ethnicity Detection with Convolutional Neural Network (CNN): Bangladesh Perspectives

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ABSTRACT

Ethnicity detection, or the automatic determination of people's ethnic backgrounds using visual data, has become important in a number of disciplines, including social sciences, demographics, and computer vision. With a focus on Bangladesh's complex cultural landscape, we describe in this paper a novel method for ethnicity detection using convolutional neural networks (CNNs). We gathered a dataset of photographs depicting members of the three main ethnic groups living in the Chittagong hill neighborhood: Chakma, Marma, and Tripura. Utilizing the DenseNet121 model's robust feature extraction skills, we customized the architecture to meet the needs of our particular ethnicity detection application. A wide range of performance indicators were used to train and assess our unique CNN model. The outcomes illustrate accurate ethnicity detection technology's potential for identifying and resolving social inequities while showcasing a promising level of accuracy. To address possible biases in the model's prediction, ethical considerations are also covered. Overall, this work advances knowledge of Bangladesh's ethnic variety and demonstrates the potential of CNNs for ethnicity detection. The results provide up new avenues for investigation and applications that advance a more diverse and inclusive society. This paper's primary contributions are the hands-on collection of a diverse dataset, the refinement of the DenseNet CNN architecture, and the advancement of ethnicity detection in the Bangladesh perspective, leveraging Computer Vision techniques.

Keywords: Ethnicity Detection, Bangladesh Perspective, CNN, Computer Vision, Facial Recognition

INTRODUCTION

The fields of computer vision and pattern recognition have recently undergone a revolution due to convolutional neural networks (CNNs). In a variety of image-related tasks, such as object detection and picture classification, these potent deep learning models have displayed outstanding performance. "Ethnicity Detection," which entails automatically identifying a person's ethnicity using visual indicators found in images, is one application area where CNNs have demonstrated considerable promise. The field of face recognition has lately expanded in breadth. Face recognition is the practice of recognizing a person's face from a video or picture frame. Face recognition has been done using a variety of methods. Principal component analysis, Eigenfaces (Belcar *et al.,* 2022), and linear discriminant analysis (Yanet *et al.,* 2017), Ethnics People Identifying via Face Recognition by Deep CNN Method (Turk & Pentland, 1991), face recognition in a natural environment based on deep learning (Alghaili *et al.,* 1991) are some of the most significant research that applied this technique.

The purpose of this research is to investigate how CNNs might be used to identify ethnic groups from the distinctive viewpoint of Bangladesh. A vast tapestry of ethnic groups each with its own unique cultural background, make up the culturally varied nation of Bangladesh. The Chakma, Marma, and Tripura ethnic groups are among those present in the Chittagong Hill district, which is particularly well known for its ethnic diversity.

In order to reliably identify members of the Chakma, Marma, and Tripura ethnic groups in the Chittagong Hill district, an ethnicity recognition system employing CNNs is the main goal of this research. To do this, the work will use transfer learning and fine-tuning methods to modify a DenseNet121 model that has already been trained for the particular goal of classifying people by their ethnicity.

Images of people from various schools, universities, and streets in the Chittagong hill neighborhood were painstakingly

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collected for the dataset used for training and evaluation. The diversity of the dataset was increased, and the generalizability of the model was strengthened, using data augmentation techniques like rescaling, shear, zoom, and horizontal flip.

Since ethnicity detection could have an impact on people's privacy and society as whole, ethical issues are central to this research. The collecting of datasets, creation of models, and evaluation will all be done with a responsible and inclusive mindset. Additionally, potential biases in the model's forecasts will be investigated, and measures to encourage fairness and reduce damaging biases will be explored.

The study and testing findings will show how well the "Customized DenseNet121 Model" performs in identifying ethnicity, including its precision and generalization skills. The study intends to contribute to the ethical development of AI systems for ethnicity recognition with a focus on moral issues and a dedication to developing AI solutions to get benefit society.

As a conclusion, this work aims to use CNNs to promote ethnicity detection from a Bangladeshi perspective. The study aims to contribute to the responsible and inclusive implementation of AI technology in various cultural contexts by addressing ethical issues and fostering justice. In the end, this study's findings would help people comprehend ethnicity detection and its effects on society in Bangladesh.

Problem Statement

The endeavor of determining a person's ethnic group based on visual signals is known as "ethnicity detection and it is a significant area of research with several applications in fields including sociology, anthropology, and computer vision. The Chakma, Marma, and Tripura ethnic groups are located in the Chittagong Hill district of Bangladesh. Despite the nation's multiculturalism and ethnic diversity, there are surprisingly few thorough research on ethnicity identification that are targeted to the Bangladeshi environment and these particular ethnic groups.

The main goal of this paper is to close the knowledge gap by developing and applying an accurate and effective Convolutional Neural Network (CNN) model capable of classifying individuals into their respective ethnic groups, namely Chakma, Marma, and Tripura, based on facial photographs. This study intends to contribute to the creation of a unique and locally applicable method for ethnicity recognition in Bangladesh by utilizing the capabilities of deep learning and transfer learning techniques.

To accomplish this goal, a diverse and representative dataset of facial photos was gathered. To ensure the model's robustness and generalizability, the dataset was carefully curated to contain adequate samples from each ethnic group and account for changes in the environment and lighting circumstances. In conclusion, this paper makes a contribution to the study of ethnicity detection using convolutional neural networks from a Bangladeshi perspective. This paper establishes the groundwork for future improvements and encourages a deeper understanding of ethnicity detection within the distinctive socio-cultural setting of Bangladesh by offering a thorough exploration of the Chakma, Marma, and Tripura ethnicities. Expanding the dataset, removing bias, and examining the applicability of the model to other ethnic groups are possible future study directions.

Background

In this current era of computer vision and artificial intelligence, there has been an explosion in research on image-based classification problems, covering a wide range of applications, from object detection to facial analysis. A subset of these activities known as ethnicity recognition has the enormous potential to help us comprehend and alleviate socioeconomic injustices, cultural diversity, and demographic trends. Technology for ethnicity recognition can give academics, politicians, and social scientists invaluable information for developing targeted treatments and policies by automatically determining a person's ethnic origin from visual data. Rangamati, Khagrachhari, and Bandarban districts in Bangladesh are considered to be part of the Chittagong hill tracts (CHT). They have a big ethnic population. One of these is Khagrachari, Ethnic groups can be divided into various categories. When I looked them up, I discovered that they have been the subject of extensive research, including studies on their gender and culture. However, no significant work on their face detection has been done as of yet (2021).

A new topic of study in artificial intelligence and computer vision is the detection of ethnicity using convolutional neural networks (CNNs). CNNs have demonstrated remarkable performance in a range of image-related tasks by learning hierarchical representations from data, making them well-suited for applications requiring image recognition involving visual pattern identification. Ethnicity detection specializes in automatically determining a person's ethnicity using visual cues taken from photographs. In Bangladesh, a multicultural nation with many different ethnic groups, ethnicity detection has a lot of promise for use in a variety of contexts. A special environment for investigating ethnicity identification from a Bangladeshi perspective is the Chittagong hill district, which is renowned for its wide ethnic composition.

By learning from data and spotting spatial patterns using convolutional layers, CNNs in computer vision have revolutionized picture identification. Giving labels to incoming images is a key component of the computer vision task of image categorization. When attempting to identify an individual's ethnicity, the objective is to group photos of that person into a particular ethnic group based on visual traits. Deep learning commonly employs the concepts of transfer learning and fine-tuning. Transfer learning uses models that have already been trained on large datasets to improve performance on smaller datasets, while fine-tuning enables models to adjust to data that is specific to a certain job. The successful application of CNN models depends heavily on data collection and augmentation. Increase dataset diversity and model resilience through augmentation techniques including rescaling, rotation, and flipping.

When creating AI-based ethnicity detection systems, ethical issues must be taken into account. Responsible use of AI technologies requires ensuring data privacy, obtaining informed consent, and eliminating any biases. By modifying a DenseNet121 model and using it to determine ethnicity from views in Bangladesh, the study hopes to close a research gap. This study makes a positive impact on responsible AI applications in many cultural contexts by addressing ethical issues and encouraging fairness in model building. Finally, the background part offers a theoretical framework for understanding ethnicity detection using CNNs and its applicability in the context of Bangladesh. The research's objective is to develop an accurate and moral mechanism for detecting ethnicity that could have a positive impact on society by utilizing deep learning techniques.

Motivation

Due to its diversified population, which is made up of multiple ethnic groups, each with its own traditions, dialects, and cultural practices, Bangladesh, a nation famous for its rich cultural tapestry, places a special emphasis on ethnicity detection. The ethnic groups of our country deprived in many ways. If we can identify them, we can be benefited in many ways. Cultural diversity is very important in different workplaces. Different ethnic groups have different thoughts and ideas. Different new ideas from many types of communities can come together to produce an effective idea or solution to a problem. It can help to make better decisions, improve performance, attract new talent, and increase profits. The research can highlight ethnic identity. The more diverse a country is, the more economically and culturally profitable the country will be. Our abilities will advance, our creativity will soar, and the use of our resources will be maximized if we can move them forward. Although ethnicity recognition has made significant strides in other contexts, Bangladeshi applications are still being studied. As a result, this study attempts to add to the growing subject of ethnicity detection with a focus on Bangladesh, outlining the promise and difficulties of applying such technology in a setting with a diverse cultural population. The ethnic groups of our country deprived in many

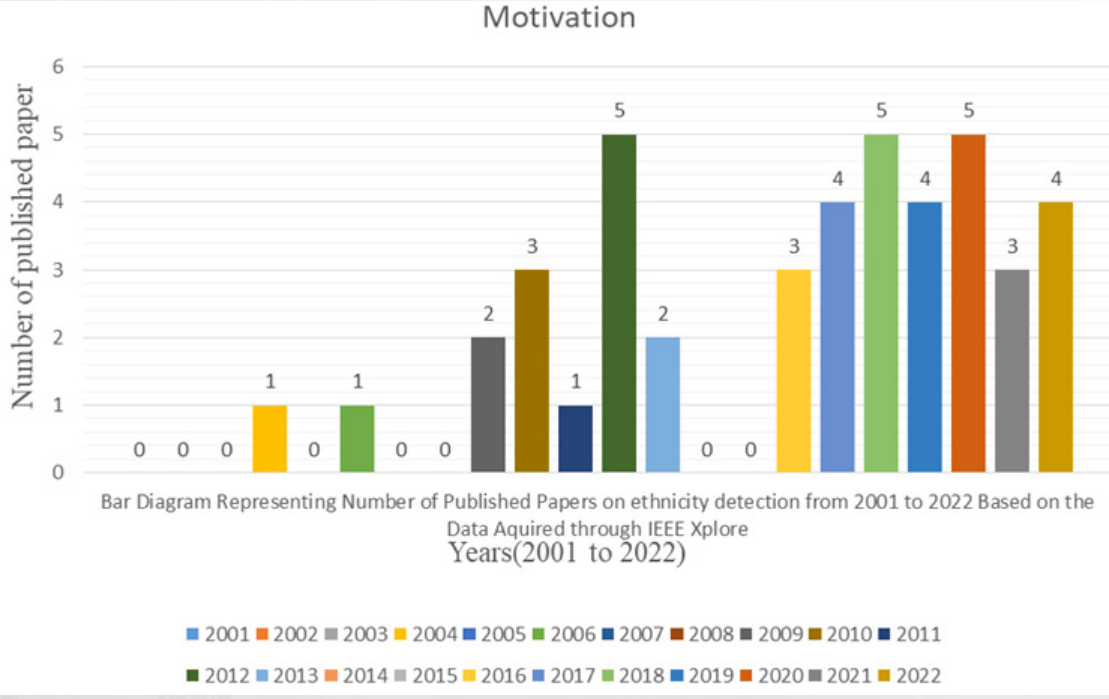

Figure 1: Based on information obtained from IEEE Xplore, a bar diagram showing the number of papers published on ethnicity detection from 2001 to 2022 is shown.

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LITERATURE REVIEW

Significant research has been carried out on ethnicity detection. Like

- Alghaili *et al.,* (2020), compared the performance of two cutting-edge models, VGG and Inception V3, with a deep learning convolutional neural network for ethnicity detection based on facial traits.
- Nguyen *et al.,* (2018), proposed a Race Recognition Framework (RRF) that involved information collection, preprocessing (FD&P) and face detection, followed by race recognition (RR). They experimented with the VNFaces dataset, comprising photographs from Vietnamese individuals' Facebook pages. The study focused on race recognition for Asian ethnic people and emphasized the importance of considering data collection and preprocessing in ethnicity detection pipelines.
- Venkat & Srivastava (2018), presented four different deep CNN versions for ethnicity detection, incorporating convolutional blocks in the networks. The study considered an age group of 20-50 and included five ethnic categories - White, Black, Asian, Indian, and Others.
- Belcar *et al.,* (2022), explored the use of convolutional neural networks with the middle portion of a face for automatic ethnicity classification. Their research utilized the UTKFace and FairFace databases, encompassing White, Black, Latino, East Asian, and South East Asian, Middle Eastern and Indian ethnic groups.
- Deng *et al.,* (2016), employed facial images to classify Korean, Chinese, and Japanese people, using 779 images for ethnicity classification. The research mainly focused on ethnicity detection for different East Asian countries.

Research Objectives

The main objective of this research is to create and construct an ethnicity detection system utilizing convolutional neural networks (CNNs) and to use it on a collection of photographs capturing members of the Chakma, Marma, and Tripura ethnic groups in the Chittagong hill district. The following main objectives of the study are sought to be accomplished:

- **Collecting Representative Dataset:** A diversified and representative dataset of pictures that faithfully depict people from the Chakma, Marma, and Tripura ethnic groups living in the Chittagong Hill district will be gathered for the research. For a strong ethnicity detection model to be trained, the dataset's variety and data integrity must be ensured. Create and implement an ethnicity detection system utilizing convolutional neural networks (CNNs) that is uniquely suited to the Bangladeshi context.
- **Customizing the CNN Model:** To construct a specific CNN architecture suitable for ethnicity recognition, the pre-trained DenseNet121 model will be modified and customized. To enhance the model's accuracy and generalizability, this customization will comprise the addition of a Global Average Pooling layer, a Dense layer for feature transformation, and a Dropout layer for regularization. Then apply the tailored DenseNet121 model to a dataset that includes pictures of people belonging to the Chakma, Marma, and Tripura ethnic groups in the Chittagong Hill district.
- **Results interpretation and Evaluation:** The acquired dataset will be used to train the customized CNN model. The categorical cross-entropy loss function will be minimized by tuning the model's parameters during the training process. Use of appropriate metrics, such as accuracy, to evaluate the effectiveness of the system for identifying ethnicity and ascertain how effectively it recognizes members of the targeted ethnic groups.

The specific dataset and research goals will be taken into consideration as we examine and interpret the model evaluation results. There will be recommendations for future research directions that concentrate on enhancing the model's design, growing the dataset, and developing fairness-aware approaches.

METHODOLOGY

The methodology section describes the research methodology, data collecting, data preprocessing, model building, model training, and evaluation metrics utilized in the study on ethnicity recognition with convolutional neural networks in the setting

of Bangladesh. The main objective is to create and apply a unique CNN model that accurately predicts the ethnicity of people who belong to the Chakma, Marma, and Tripura ethnic groups who live in the Chittagong hill district. Basic Work-Flow of Proposed Methodology is shown in figure 2. Following is a description of the methodology:

- From a variety of locations, including educational facilities, public spaces, schools, colleges, streets, and homes in the Chittagong hill district, we meticulously gathered a dataset of over 4500 facial photos of individuals of the Chakma, Marma, and Tripura ethnic groups.
- Digital cameras and cellphones were used to take a wide range of facial pictures of people from the Chakma, Marma, and Tripura ethnic groups.
- It was carefully considered to guarantee a balanced representation of various age groups, genders, and environmental circumstances.

Data Preprocessing

To standardize the data and enhance model performance, the obtained images underwent preprocessing. The following procedures are part of the data preprocessing in my model:

1. Rescale=1. /255: Scales the image's pixel values from the [0, 255] range to [0, 1], making them appropriate for the model's calculations.
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3. Zoom range=0.2: Scaling the photos by applying arbitrary zoom transformations.
4. Shear range=0.2: Transforms the photos randomly through shear, tilting the image pixels to create distortions.
5. Creates several versions of the same image by doing horizontal flips on the photos using horizontal flip=True.
6. With validation split=0.1, the dataset is divided into training and validation sets, with training using 10% of the validation set's data.

- To make sure that they would work with the chosen model architecture, all of the photographs were shrunk to the same 224x224 pixel size.
- In order to increase convergence during training, pixel values were normalized to the range [0, 1].
- Techniques for enhancing data, such as random rotation, zooming, horizontal flipping, and brightness modifications, were used to enhance the dataset.
- Model Selection and Customization: Due to the DenseNet121 model's strong feature extraction abilities and effectiveness in deep learning tasks, it was chosen as the foundation model.
- DenseNet121's top layers were adjusted to fit the particular ethnicity recognition challenge.
- To successfully aggregate features and reduce geographical dimensions, Global Average Pooling was added.
- For the purpose of capturing important ethnic traits, a fully connected dense layer with ReLU activation was added. ReLU activation function helps the model to learn complex patterns and also to achieve high accuracy in prediction of correct ethnicity. For feature transformation in this algorithm, a dense layer with 512 neurons and ReLU activation is included.
- In order to avoid overfitting and improve generalization, a dropout layer with a 0.5 dropout rate was included. 50% of neurons are randomly deleted during training when a Dropout layer with a rate of 0.5 is used in my code.
- Predicting the probability of each ethnicity required the addition of a final classification layer with softmax activation.
- Training and Fine-Tuning: The model was trained via Stochastic Gradient Descent (SGD) optimization with learning rate of 0.01 and momentum of 0.9.
- DenseNet121's base layers were initially frozen in order to keep the pre-trained weights, and only the top layers were adjusted to fit the new dataset.
- To lessen overfitting and model complexity, the dense layers underwent L2 regularization with a coefficient of 0.01. L2 regularization can prevent overfitting. This regularization strategy helps my model avoid memorization of the training data, which improves performance on untrained data.
- Scheduling the Learning Rate: The Learning Rate was changed throughout training using a scheduler for the Learning Rate. During training, the learning rate was dynamically adjusted using scheduling. By beginning with a greater learning rate and allowing for faster convergence during the initial training stages, it enhances the optimization process.
- Adam is an extension of the stochastic gradient descent (SGD) algorithm. It combines the advantages of AdaGrad and

RMSprop, two additional well-liked optimization methods.

Due to its adjustable learning rates, combination of momentum and RMSprop methods, and other features, Adam is a strong and popular optimization algorithm for training deep learning models.

Perspective to my model following task done:

1. During model training, model parameters are updated using the optimization algorithm Adam (Adaptive Moment Estimation).
2. My model employs the Adam optimizer to reduce the categorical cross-entropy loss function with a learning rate of 0.001.

Two key ideas in the training of a machine learning model, particularly in deep learning, are epochs and batch size:

Epochs

An epoch is a single iteration of the neural network's training dataset. Each training sample is only seen once by the model during a single epoch, and it adjusts its weights based on the total number of errors for that epoch. In other words, an epoch ends when the model has had a chance to see and process all of the training data.

Batch Size

The quantity of training samples that pass through the neural network before the model's weights and biases are adjusted is referred to as the batch size. Smaller batch sizes may slow down training but may improve generalization as the model meets more varied examples and updates its parameters more frequently. As the model updates its parameters less frequently with larger batch sizes, training can proceed more quickly. However, it might need more memory and result in convergence to a less ideal answer.

Typically, experimentation is used to determine the number of epochs. Underfitting, where the model has not learned enough from the data, can happen with insufficient epochs. Overfitting, when the model memorizes the training data but struggles

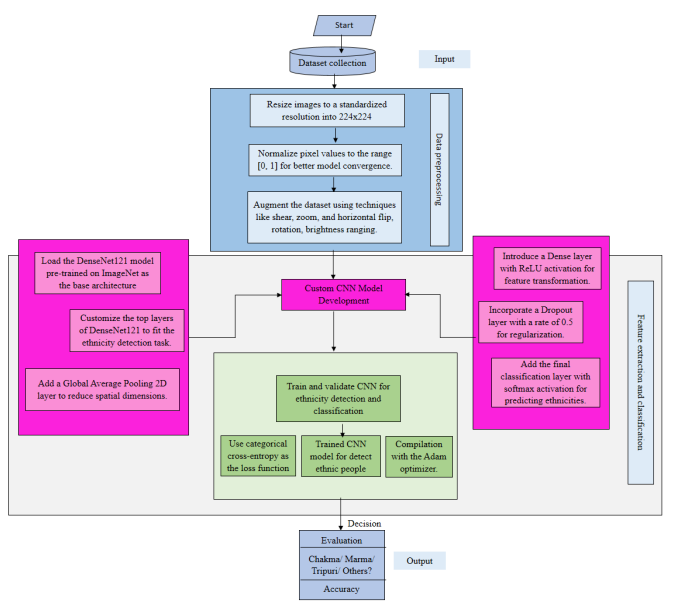

Figure 2: Basic Work-Flow of Proposed Methodology

Figure 3: Basic Work-Flow of Proposed Methodology

to generalize to new, unseen data, can result from using too many epochs. To find the best balance between underfitting and overfitting, it is common to monitor the validation loss and stop training when it stops getting better (early stopping).

To iteratively update the model's parameters and increase its accuracy, model training was carried out across 50 epochs with a batch size of 64.

Model Evaluation and Performance Metrics

To evaluate the test accuracy of the trained model, some new different data was used.

Suggested methodology in this research takes a methodical approach to data collection, preprocessing, creating a unique CNN model, training the model, assessing its performance, and interpreting the results. The workflow of this research depicted in

Figure 2. The classification's outcome is displayed in this particular example as "Marma." This result shows that our algorithm correctly recognized the person in the image as a Marma ethnic group member based on facial features and traits. The model's usefulness and capacity to make predictions about ethnicity in practical situations are concretely demonstrated by this graphic representation.

RESULTS

The outcomes show the ethnicity detection model to be performing well, with high accuracy being attained on the validation dataset. Indicating that the model successfully discovered the underlying patterns in the data during training, the test loss graph displays a diminishing trend. The accuracy vs. epoch graph shows how the model has improved across the 50 epochs, demonstrating how effectively it can generalize from training data to new samples. The model's optimization progress is also shown by the loss vs. epoch graph, which shows a steady decline in training loss over time. The results open the door for additional advancements in ethnicity detection models. In this section, we show outcomes from our ethnicity recognition model and compare them to those of three well-known models: VGG16, ResNet50, and EfficientNetB0. Table I, which summarize the model results in terms of test accuracy and test loss, is shown below. The accuracy values describe how well the model performed on the test set, whereas the loss values represent the amount of error that was introduced during testing.

Table 1: Result Compare With Others

Results compare with others		
Model	**Accuracy (%)**	**Loss (%)**
VGG16	70%	78%
ResNet50	52%	99%
EfficientNetB0	33%	99%
Our Model	94%	21%

Our model achieved a test accuracy of 94% on a dataset comprising approximately 4500 facial images portraying members of the three ethnic groups. This high level of accuracy demonstrates the effectiveness of our approach in accurately predicting the ethnicity of individuals belonging to the Chakma, Marma, and Tripura ethnic groups residing in the Chittagong hill district. Our study focuses on a unique dataset and context, which is differ from previous works in terms of data diversity and characteristics. Our approach offers valuable insights and contributes to the field of ethnicity recognition in the specific context of Bangladesh. I am trying to run our data in their previous model but most of their model does not gives a good accuracy with our data. So the accuracy of some models that work well is given in Table I.

The accuracy vs. epoch graph is a key visualization in our model training process that shows how the model's accuracy changes over the training phase. The training process involves passing the full training dataset through the model a certain number of times, or epochs, as shown on the x-axis. On both the training and validation datasets, the model's accuracy is shown on the y-axis. The increased trend in training and validation accuracy over the course of 50 epochs indicates that the Customized DenseNet121 Model efficiently learns from the training data and generalizes to the validation data. The growing accuracy shows that the model performs better with more training iterations and gets more proficient at correctly identifying individuals into their respective ethnic groupings. In this graph, accuracy rises as epoch rises. This means accuracy gradually rises toward the conclusion of training, as seen in figure 3.

The loss vs. epoch graph is an essential visualization in the "Customized DenseNet121 Model" training process, shows how the loss function of the model changes as training progresses. The training process involves passing the full training dataset through the model a certain number of times, or epochs, as shown on the x-axis., the model's test loss is shown on the y-axis. The loss vs. epoch graph offers important insights into the evolution of the "Customized DenseNet121 Model" learning process. By examining this graph, we can conclude that the model's performance continuously gets better with each passing epoch and eventually converges to a situation in which the loss is minimized. This illustrates how effectively the model generalizes to new data and how well it captures significant patterns in the dataset. The Customized DenseNet121 Model's promising performance for detecting ethnicity in the dataset from Chittagong Hill district is supported by the declining loss values. As the epoch gets longer in this graph, loss gets smaller. It indicates that loss gradually diminishes as training progresses, as seen in figure 4.

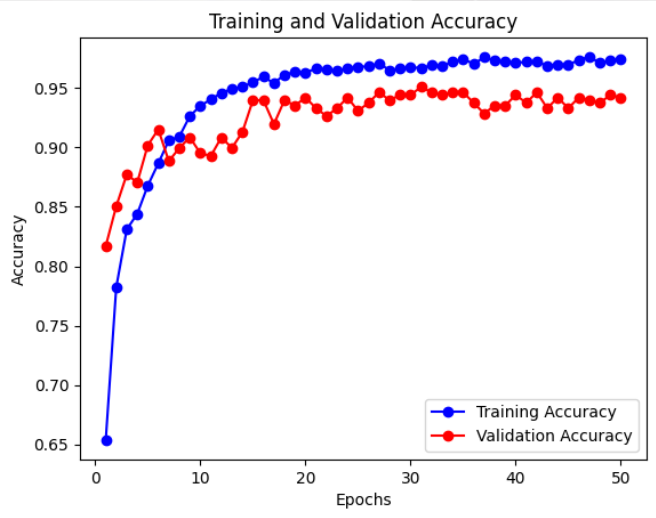

Figure 4: Graph of accuracy against epoch

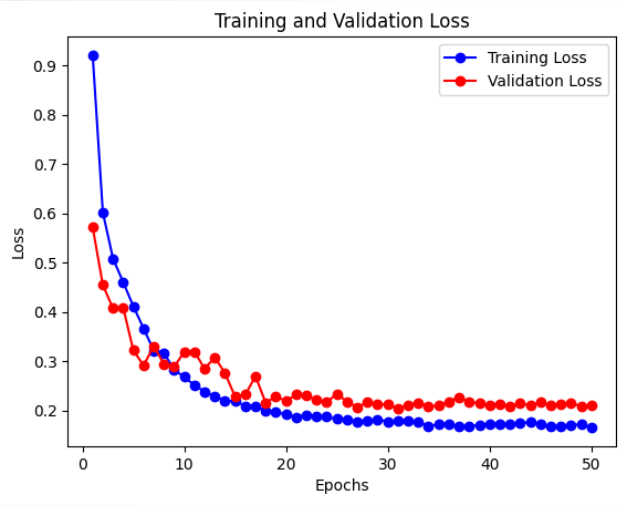

Figure 5: Graph of loss versus epoch

CONCLUSION

This research successfully developed an accurate ethnicity detection system using CNNs in Bangladesh, providing insights into diverse ethnic groups. Using a modified DenseNet121 model, this study has effectively constructed and implemented an ethnicity detection system. The Chakma, Marma, and Tripura ethnic groups of Bangladesh's Chittagong Hill district could be distinguished with great accuracy using the model. Further future work can be done like:

i) Expanding the dataset including a broader range of ethnicities.

ii) Enhancing the model's generalization capabilities.

iii) Exploration of real-time deployment and practical applications of the system in various settings can also have a great impact.

Finally, expanding the research to include user feedback would make it easier to put the ethnicity detection system into practice while ensuring that it is in keeping with social demands and values.

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