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Department of Software Engineering

Lip Print Identification Using Deep Learning

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APPROVAL

This project titled on "**Biometric Lip print-based identification using deep learning**", submitted by **Hasib Ahmad Bhuyan (ID: 203-35-681)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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Declaration

I hereby declare that this thesis is submitted in partial fulfillment of the requirements for the B.Sc. in Software Engineering at Daffodil International University, under the supervision of Tapushe Rabaya Toma, Assistant Professor, Department of Software Engineering. I affirm that this is my original work and has not been submitted elsewhere for any degree or diploma.

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Abstract

The idea behind biometric identification is that every person has distinct qualities. While iris, retina, fingerprint, and face recognition are common traditional ways, an alternative Lip-based identification is a method that uses the permanent patterns on human lips as a biometric measurement. It takes a lot of work to physically collect lip prints. By taking higher-quality pictures rather than relying on lip print detection, we can accomplish this more quickly and efficiently using convolutional neural networks & computer vision.

The purpose of this research identifies people only by their lip prints. Our suggested approach makes use of the convolutional neural network (CNN) capacity to recognize and extract distinctive characteristics from lip prints. We use data augmentation and transfer learning approaches to overcome the issues of limited data availability and variability in lip print images.

Several deep learning models were employed here. With Resnet50, I achieved 97% accuracy. It was discovered that employing VGG 19 and achieving 93% accuracy as well as using Inception Net and achieving 98% accuracy.

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CHAPTER 1 – INTRODUCTION

1.1 Background

The use of lip prints to identify an individual dates back early 20th century The use of lip prints to identify an individual dates back early 20th century. It is noteworthy that the biologist R. Fischer in 1902, for the first time, described the biological nature of systems of the ruts on the red part of human lips [1]. However, it was not until 1932 that the French criminologist Edmond Locard embraced the use of lip prints in the identification of a person [2]. The idea of utilizing the folds and ridges of the lips as a means of physically identifying a person, like the fingerprint, was proposed by the forensic scientist Le Moyne Snyder in 1950 and he is recognized as 'Cheiloscopy's' patron [3]. In 1960 Dr. Martins Santos advocated the lip characteristics to be employed for the identification of a person and also offered a plain form of classification [4,5]. Lip prints were first studied in Hungary in 1961 when lip traces were left at the crime scene and lip prints had been found to be effective in identification [6]. A lot of work on lip prints has been done from the year 1950 onwards especially by Japanese scientists including Yasuo Tsuchihashi and Kazuo Suzuki to find out about the forensic odontological relation of female lips and lipstick [7,8]. For a long time, different classification schemes and analysis methodologies have been applied to lip prints for purposes of identification, which include the common features method, the photographic montage, and the contour methods.

1.2 Problem Statement

Research has revealed that the ridges on a person's lips remain stable throughout their lifetime, making lip print patterns a viable biometric for identification purposes. There are four main types of lip print patterns - the line pattern, intersected pattern, branch pattern, and reticular pattern - which vary based on gender and the anatomy of the mouth.

1.3 Research Questions

1. Can do lip print identification without traditional methods

2. Can people be classified with digital lip images?

3. Can lip identification be done with deep learning?

4. Can model evaluation be done with different matrices?

1.4 Research Objectives

1. To develop techniques and methods that can classify and differentiate between different lip print patterns.

2. To establish a lip print classification system that can effectively classify between individuals based solely on their lip print biometric

3. The accuracy of the developed system will be evaluated using appropriate performance metrics to ensure its effectiveness in accurately classifying lip prints

1.5 Thesis Organization

Deep learning techniques have significantly enhanced lip print identification by providing sophisticated algorithms like CNNs for accurate pattern recognition from lip images.

These cutting-edge approaches offer a new perspective on secure authentication and identification procedures while improving reliability. Deep learning-based lip print identification is emerging as a major biometric technology, providing a robust and innovative method for human recognition.

CHAPTER 2 – LITERATURE REVIEW

2.1 Early Approaches in Lip Print Analysis

One of the earliest bases for pattern-based lip print classification was established by Santos (1967) [9,10]. As seen in the studies of Suzuki and Tsuchihashi (1970). Researchers focused on the subjectivity and inconsistency associated with manual analyses, which include potential human errors in addition to being highly subjective, even though they first raised the possibility of using such prints for forensic purposes through such studies.

2.2 Advancements in Digital Image Processing

From the time that digital image capabilities were developed, researchers have been studying automated lip print identification algorithms. A number of methods, including image enhancement, edge detection, and pattern recognition, were employed to digitize lip prints for study. Research by Sharma et al. (2010) and Vats et al. (2013) demonstrated the potential of digital image processing to improve the precision and repeatability of lip print analysis [11,12]. Still, these methods persisted.

2.3 Emergence of Machine Learning Techniques

A significant advancement is the integration of machine learning into lip print identification. Machine learning algorithms support vector machines (SVM) and k-nearest neighbors (k-NN) were applied to classify and match lip print patterns. These approaches, as seen in the works of Verma et al. (2014) and Anand et al. (2016), showed improved performance over traditional methods [13,14]. However, the majority of the feature extraction procedure was still done by hand and took a long time, which limited how far these approaches could be taken.

2.4 Deep Learning Revolution

The breakthrough in lip print identification came with the application of deep learning, specifically convolutional neural networks (CNNs). Deep learning models may automatically learn from raw photos and extract features. CNNs are very good at collecting spatial hierarchies within images due to their hierarchical structure, which qualifies them for lip print analysis.

Studies by Rathore et al. (2017) and Puri et al. (2019) demonstrated the effectiveness of CNNs in lip print identification, achieving high accuracy rates and robustness to variations in lip print quality [15,16]. These models' performance on fresh, untested samples is well-generalized because they were trained on big lip image datasets. This indicates that deep learning models designed for lip print recognition perform better when data augmentation and transfer learning approaches are improved.

2.5 Comparative Analysis and Current Trends

As evidenced by studies conducted by Kumar et al. (2021) and Gupta et al. (2022), which demonstrate notable improvements over underperforming transdisciplinary disciplines like elucidation science, the literature in recent years has focused on a variety of approaches within deep learning, such as from classical machine learning methods up to modern AI [17,18]. This statement implies their effectiveness when used appropriately or incorrectly as well. Current research endeavors to enhance the explainability of these models and enhance security by creating multi-modal biometrics that use lip prints in addition to other biometrics.

Farrukh and van der Haar's 2022 IET Biometrics study explores lip prints as a biometric, blending traditional and deep learning methods [19].

The research aims to enhance the accuracy and reliability of lip print identification by combining Traditional Machine Learning techniques and advanced Deep learning. This study contributes to the evolving biometric identification landscape, with broader implications for the field.

The main purpose of this research is to enhance the accuracy and reliability of lip print-based identification systems. With advanced deep learning models, the study aims for more accurate results in lip print identification.

CHAPTER 3 – RESEARCH METHODOLOGY

By emphasizing lip prints as a distinctive identifier, the thesis methodology for lip print identification using deep learning takes a complete approach to improving facial recognition technology. Data collection, preprocessing, model training, and evaluation for both masked and unmasked facial recognition are all included in the technique.

I have divided my dataset into two parts here. Training and testing. Since there were not enough images for each class, I did data augmentation and trained then classified the original data with this data.

3.1 Dataset Collection

Here I have used the Chicago Face data set. At the University of Chicago, Debbie S. Ma, Joshua Correll, and Bernd Wittenbrink created the Chicago Face Database [20]. The purpose of the CFD is to support scientific investigations. It offers standardized, high-resolution images of the faces of men and women of different ethnic backgrounds, ranging in age from 17 to 65. The main CFD set consists of images of 597 unique individuals. They include self-identified Asian, Black, Latino, and White female and male models, recruited in the United States. All models are represented with neutral facial expressions. However, I have worked with only 367 unique individuals.

3.2 Dataset Preprocessing

In data preprocessing, I have taken the help of Computer vision [21]. Computer vision is a field of computer science that focuses on enabling computers to identify and understand objects and people in images and videos.OpenCV provides a real-time optimized Computer Vision library, tools, and hardware.

In order to improve detection, I convert the image to grayscale. I also utilize the Dlib library [22]. Basically, landmark extraction and face detection are its uses. However, I've used this to isolate the human face's lip region. I uses the coordinates of the landmarks (landmarks 48–67) that correlate to the lips to extract the lip region from the image.

Then I use the image augmentation technique. Image augmentation is a step where augmentations are applied to existing images in the dataset. This procedure can enhance the model's capacity for generalization, enabling it to function better on unobserved images.

I have used several augmentation functions, Flipped the images, and Scale images by a given factor. Adjusts the brightness and contrast of the image. Applies the edge enhancement and rotates the image by 180 degrees. Randomly flips the image horizontally or vertically.

My dataset has 367 classes after augmentation, with 711 photos for training and 7110 images for testing. I'm using a variety of Deep learning models for this.

3.3 Algorithm

Following data preprocessing, I applied a variety of deep learning models to this. Specially, Convolutional Neural Network [23,24]. a convolutional neural network (CNN/ConvNet) is a class of deep neural networks, most commonly applied to analyze visual imagery. CNNs are particularly good at processing input with a topology resembling a grid, like images. It is made up of a grid-like arrangement of pixels with pixel values to indicate the color and brightness of each pixel.

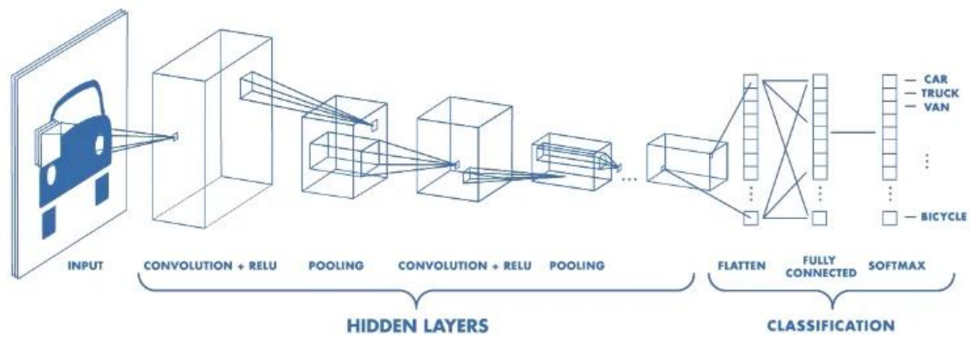

Figure 1: CNN Algorithm

A CNN typically contains three layers, they are; a convolutional layer, a pooling layer, plus a fully connected layer. It is considered the basic unit of a CNN because of its convolutional layer. These contain learnable filters (or kernels), which are affected by a small receptive field but extend the full depth of input volume. The input data is then fed into a number of small receptive fields, which are also referred to as pooling windows in Pooling Layers. The fully connected layer means the connections are defined between all neurons of neighboring layers. This means that every neuron in one layer is connected with all others in other layers, therefore each neuron takes an input from complete previous or next layers.

activation functions fix the output, add non-linearity in the activation and also enforce a specific structure of sparsity in the activation of the network. The functions are sigmoid, tanh, reLU, and softmax are common examples; they each have their own characteristics. In the development of neural networks, the activation function is a critical decision due to its influence on the model.

Three popular CNN models—Resnet50v2, Inceptionv3, and VGG 19—are used in my thesis.

ResNet50V2:

ResNet50V2 is a Convolutional Neural Network (CNN) architecture that is designed for Image Classification. It is a variant of the popular ResNet50 model which is known for its use of residual connections to address the vanishing gradient problem in deep neural networks. The ResNet50v2 has around 25.6 million parameters and it also has a similar overall structure with ResNet50 [26].

The ResNet50V2 model, trained on ImageNet dataset, serves as the basis for this model architecture while a pre-trained ResNet50V2 is made available for transfer learning. Additionally, the frozen pre-trained layers in ResNet50V2 imply that their weights are not modified as the training progresses, leveraging on features extracted from the big ImageNet dataset, important in different image classification tasks. I added customized classification layers on top of the base model ResNet50V2. These contain a global average pooling layer that reduces the size of feature maps spatially thereby reducing the chances of overfitting.

InceptionV3:

InceptionV3 refers to a strong deep learning model introduced by Google in the family of Inception to be used in image recognition. In other words, InceptionV3 is a type of CNN whose primary function is to classify the key attributes of images while determining if they are conveying objects, scenes or other concepts [27]. The proposed model equipped with the “Inception module” can identify features at multiple scales at once and thus can take benefit of both global and specific knowledge. Also, the InceptionV3 model incorporates features that include factorized convolutions, and increased regularization that ensures that the model does not have too many layers, while at the same time having improved performance. The outcome is self-explanatory and therefore it can be stated that InceptionV3 has had its outstanding performance and has reached more than 78% of the top-1 classification of the ImageNet dataset.

In addition to the measure of performance, the major advantage of using InceptionV3 lies in its flexibility where developers can readily fine-tune the network to address a myriad of image recognition issues with a less amount of training data in comparison to the original dataset used to train InceptionV3 network. All in all, the I suppose that InceptionV3 is a high-performance deep learning model that has become a good reference for deep learning researchers and engineers through pioneering the new architecture design and efficient learning with high-performance image classification.

VGG19:

VGG19 is a deep convolutional neural network (CNN) that has been designed at the Visual Geometry Group of the University of Oxford. This depth enables the model to be able to learn features that are quite complex, and therefore makes VGG19 to be more appropriate for modeling complex image classification [28]. Nevertheless, added layers enhance complexity over the convolutional models such as the VGG16.

It is a version of VGG containing several convolution and pooling layers: convolution layers extract certain features, while pooling layers decrease the dimensionality of space and add to the model's stability. VGG19 has been pretrained on high dataset such as ImageNet, it can be used for feature transfer learning that involves using the features learned without much recalculation for a new task.

In the present work, to introduce more spatial details, I have used flattening layer in place of the global max pooling layer in the original architecture of VGG19 for the learning of more sophisticated characteristics of the data. I also used the batch normalization to make training stable and the dropout to avoid overfitting. Such improvements are made with an objective of increasing precision and variability.

The model is trained with Categorical Cross-Entropy loss and optimized with Adam then a softmax activated layer is added for the classification. This is done through fit() method accompanied by the use of a generator to process the data.

In future work, detailed examination of the model will be carried out to compare its efficiency while working with amplified populated data samples.

3.4 Model Evaluation:

In the context of lip print identification, evaluating the performance of deep learning models like ResNet50, Inception, and VGG19 is critical for ensuring the reliability of the classification results. Among the various evaluation methods, the confusion matrix stands out as a comprehensive tool that provides insights into the model's predictive capabilities [25].

A confusion matrix is a tabular representation that compares the actual labels with the predicted labels generated by the model. It consists of four key elements:

- **True Positives (TP):** Correctly identified positive cases (e.g., correctly identified lip print matches).
- **True Negatives (TN):** Correctly identified negative cases (e.g., correctly identified non-matches).
- **False Positives (FP):** Incorrectly identified positive cases (e.g., non-matches incorrectly identified as matches).
- **False Negatives (FN):** Incorrectly identified negative cases (e.g., matches incorrectly identified as non-matches).

Using the confusion matrix, various performance metrics can be derived to assess the effectiveness of the models:

- Accuracy: The overall correctness of the model, calculated as (TP + TN) / (TP + TN + FP + FN).
- Precision: The ratio of correctly predicted positive observations to the total predicted positives, TP / (TP + FP).
- Recall : The ratio of correctly predicted positive observations to all observations in the actual class, TP / (TP + FN).
- F1-Score: The weighted average of precision and recall, providing a balance between the two, 2 × (Precision × Recall) / (Precision + Recall).

Lip prints are usually very close in patterns and hence can only be easily distinguished by this model through the use of these metrics. For example on the aspect of precision it is important to ensure that the times the model scores a match then it must be the right one so that there are minimal wrong identifications. High recall guarantees that the model will not ‘overlook’ actual matches and is very important in scenarios such as forensic use.

Evaluation of ResNet50, Inception and VGG19 models on lip print data set was done by confusion matrix in this research. On the basis of the confusion matrices it was possible to understand which specificities of the models were causing the misclassification and how we could improve the models in the future. For instance, if in the confusion matrix some of the features represented a high value of FNs it would mean that it is time to change the structure of the model or the way the data is preprocessed in order to improve the recall.

The confusion matrix in this context gave a more detailed comparison and identification of the short comings of each the models in identifying lip print. This way, the selected model is not only precise but also recalled all the most important aspects necessary for efficient practical usage of the model where both precision and recall are valuable.

CHAPTER 4 – RESULTS & DISCUSSION

Resnet50:

The test dataset evaluation of the ResNet model revealed a test loss of 0.2385 and an accuracy rate of 95.78%. The F1-score stands at 0.9436 as the model's accuracy rate is balanced revealing a precision of 98.47% and recall rate at 90.58%. Classifying tasks demonstrate high accuracy and equilibrium performance.

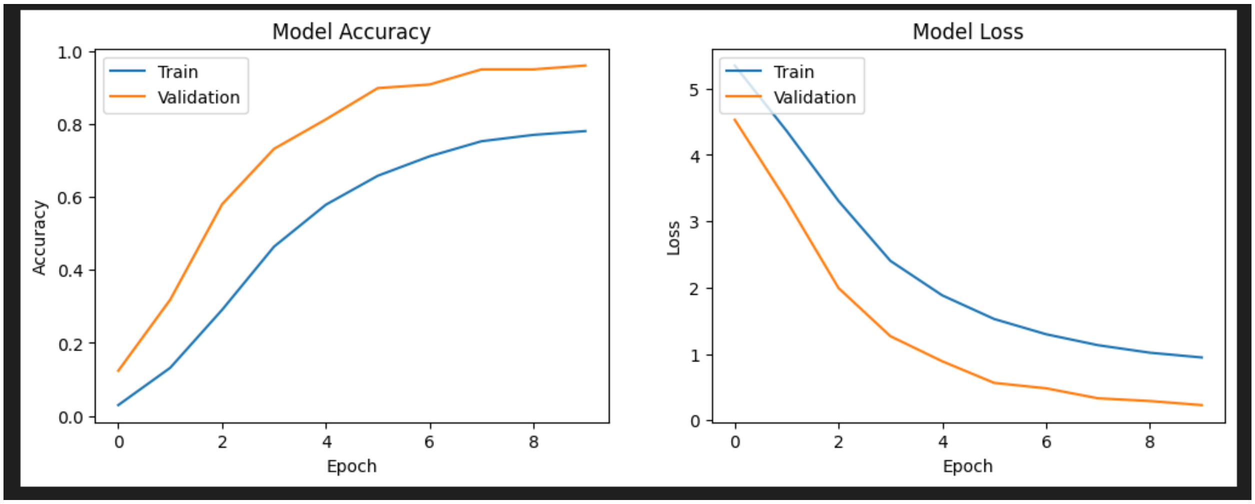

Figure 2: Results (Resnet50)

Inception V3:

The test accuracy obtained by the Inception V3 model when evaluated on the test dataset was 98.45%. In addition to that, the model's precision was 99.13% while the recall stood at 96.48%..This implies that Inception V3 model has been so good at classifying items because it has shown strong accuracy along with correctness.

Matrics	Accuracy	Precision	Recall	F1 Score
Result	98%	99%	96%	97%

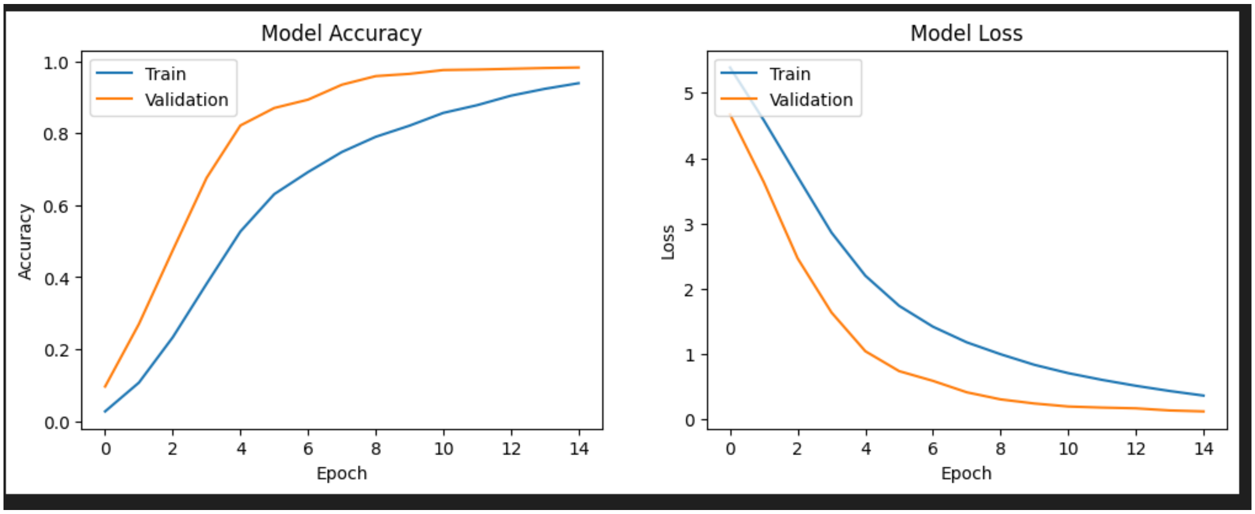

Figure 3: Results (Inception V3)

VGG 19:

The VGG19 model was evaluated against datasets during testing which gave an accuracy figure of 93.11%. Specificity obtained was 99.43% while sensitivity stood at 74.12%. Therefore we got an F1-score equal to 0.8493 from the formula that combines both precision and recall metrics into one measure [ref]." From the above formulas you can see where our strength lies; we have very good precisions but poor recalls with regard to this mode (VGG19). This means that even though this method has very high specificity it has low sensitivity making it have a medium F1-score thus showing an area which has to be enhanced in order to recognize more such cases.

Matrics	Accuracy	Precision	Recall	F1 Score
Result	93%	99%	74%	84%

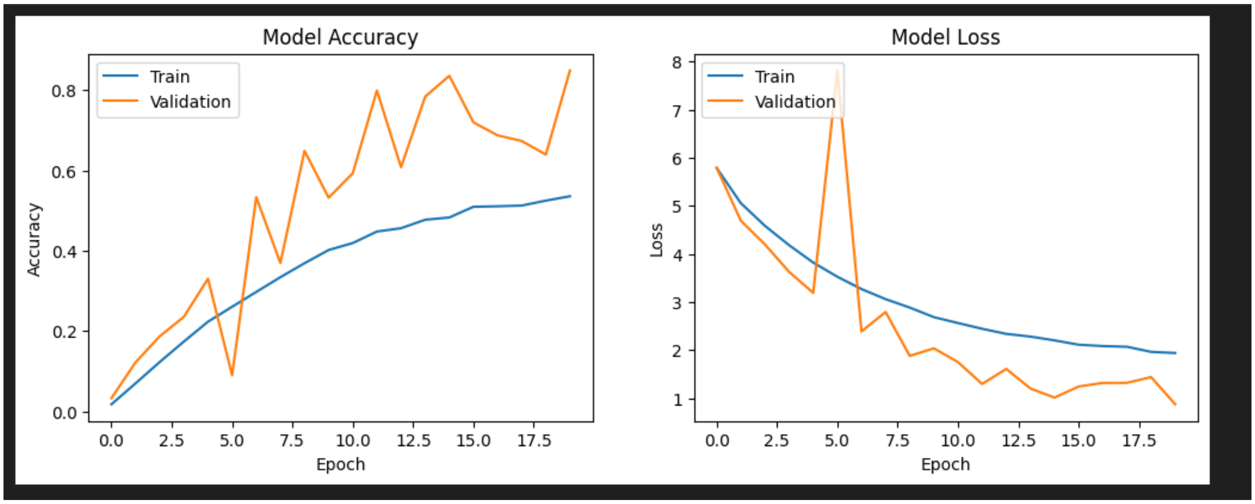

Figure 4: Results (VGG 19)

CHAPTER 5 – CONCLUSIONS & RECOMMENDATION

In conclusion, generalization of deep learning models such as, VGG16 and Inception V3 which have high accuracy can be recommended for lip print identification. These models present a considerable opportunity to develop forensic science, which will help improve the identify strategy, and is a highly automated system. The results for this study could be expanded on in subsequent studies, by aiming to achieve even higher rates of recall and consider the implementation of these models in forensic practices, possibly in conjunction with other biometric identification methods for increased identification reliability.

These outcomes make a positive contribution to the existing repertoire of information regarding the use of deep learning regeneration for biometric identification; it eventually shows how complex neural network structures can profoundly improve the effectiveness of forensic studies.

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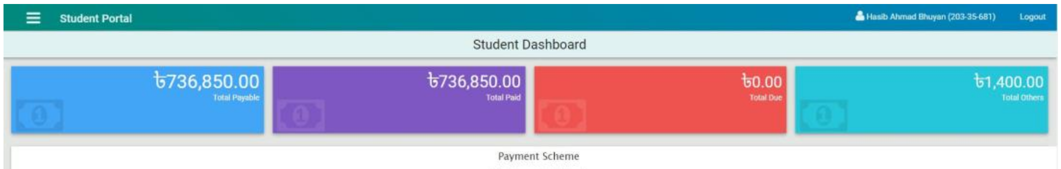
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