Facial Matching and Reconstruction Techniques in Identification of Missing Person using Deep Learning

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***Abstract*— The number of missing person cases has dramatically increased nowadays, leaving loved ones with a lot of unanswered questions. Police inquiries and public announcements are two regularly used traditional methods for locating missing persons, although they frequently fall short, especially over time. Artificial intelligence (AI) is gaining popularity and could be used to enhance the search process. This study offers a revolutionary approach for solving the unsolved cases of missing individuals by using AI-based facial matching and face reconstruction approaches. The proposed method successfully uses the ORL (Olivetti Research Laboratory) Dataset's Support Vector Machine (SVM) classifier to reach an outstanding accuracy of 93% by combining face landmarks and machine learning algorithms. Additionally, a 3D face reconstruction method based on Convolutional Neural Networks (CNN) trained on the varied 300-W dataset achieves a high accuracy of 90%. These results demonstrate the potential of AI and deep learning models for improving missing person identification. The proposed approach offers a viable option that aids in providing closure to the impacted families, making a significant contribution to the field and reducing crimes in the future.**

Keywords*— *Facial Landmarks, Face Reconstruction, Support Vector Machine, Convolutional Neural Networks, Missing persons

I. Introduction

Finding missing persons is a critical task for law enforcement agencies and search-and-rescue organizations. Time is of the essence in such cases, as delays can significantly diminish the likelihood of a safe recovery. Traditional methods, while essential, often rely on labor-intensive processes such as canvassing vast areas or relying solely on public appeals for information. These methods are not only resource-intensive but also heavily reliant on human memory and cooperation. Additionally, the exponential increase in the number of missing person cases and the challenges of existing methods, such as scalability, the need for extensive human intervention, and limited accuracy in complex scenarios, highlight the importance of exploring advanced technologies like AI, which have the potential to address these challenges and significantly improve the effectiveness and efficiency of missing person identification efforts.

Efforts to address this pressing issue have increasingly turned towards advanced technologies, with a particular emphasis on artificial intelligence (AI) applications. In recent years, AI has emerged as a promising solution to augment traditional search methods. AI systems can analyze vast amounts of data [1], including social media posts [2], surveillance footage [3], and other digital traces, to identify patterns and generate leads. By automating data processing and analysis, AI algorithms can significantly reduce the time and effort required to sift through information, enabling search teams to focus on actionable leads promptly.

However, it is important to acknowledge the existing methods and technologies that have been employed in missing person identification. Traditional facial recognition techniques have played a significant role in matching images of missing individuals with available databases, allowing for potential identification. While these techniques have limitations with low-quality or partial images and in cases where significant time has passed since the disappearance. To overcome these limitations, data analysis approaches have emerged as a valuable tool [4]. Data analysis approaches using machine learning algorithms analyze large volumes of data, including images, location data, and social media activity, to find patterns and connections. These approaches can uncover leads, such as identifying individuals in proximity or detecting behavioral patterns. Technological advancements have a significant im- pact beyond search operations. For families of missing individuals, AI-powered search techniques offer hope by expediting the search process and bringing loved ones back home sooner. This timely resolution alleviates emotional strain, enabling families to heal and find closure. Find Me Group (FMG), which is located in the United States, is a prominent organization focused on addressing missing individual cases. By leveraging advanced technologies and their deep understanding of the complexities involved, FMG strives to improve search outcomes and bring relief to affected families.

This study aims to explore the integration of advanced techniques [5], including machine learning, deep learning, and facial reconstruction, to revolutionize the search for missing persons. Harnessing the power of these cutting-edge technologies may provide crucial insights into the whereabouts of missing individuals. The percentage of missing people continues to rise steadily, as depicted in Fig. 1. This upward trend underscores the urgent need for innovative and efficient solutions. By integrating AI into the search process, the objective is to develop a dependable and user-friendly system that assists law enforcement agencies in rapidly locating missing individuals [6].

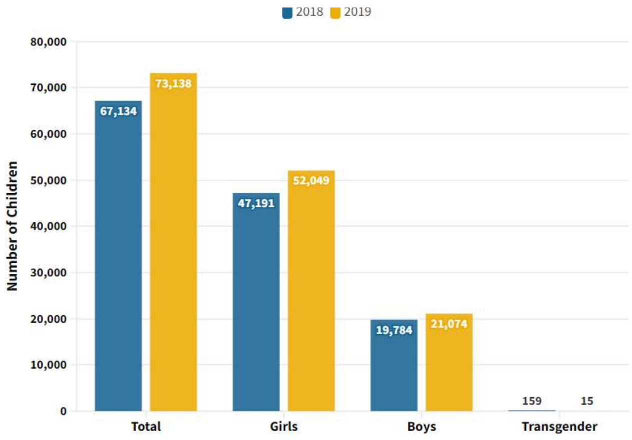


Fig. 1. Number of Children reported "Missing" by Gender (2018 vs 2019)

In addition to the immediate benefits for law enforcement and search-and-rescue groups, the integration of advanced technologies like 3D facial reconstruction using computer vision holds tremendous potential. Beyond aiding in the identification process, this technique offers applications such as facial recognition, animation, and virtual reality [7]. The proposed model for face reconstruction uses Convolutional Neural Networks (CNN), a powerful deep learning architecture widely used in computer vision tasks. In the medical field, CNNs have been successfully applied to tasks such as medical image analysis, diagnosis, prognosis [8], ultrasound image classification [9] and diabetes mellitus prediction [10]. In addition to CNNs, other deep learning techniques like Generative Adversarial Networks (GANs) and Autoencoders are being explored for 3D face reconstruction. GANs can generate realistic 3D face models from 2D images, while autoencoders can reconstruct 3D faces from partially obscured or low-resolution images [11].

II. Relate Works

A new model, FLAME, has been developed for 3D face modeling with the aim to bridge the gap between advanced and basic methods in the field. The FLAME model underwent training using over 33,000 scans, and researchers compared its performance to that of other models like the Basel Face Model and the Face Warehouse model. The results demonstrate that FLAME is significantly more efficient and accessible for use in research projects [12]. A new approach has been developed for construction without using a sizable face texture library; single-view pictures are used to create 3D facial forms with high-resolution textures. By adding face characteristics from the input image, this technique enhances the basic texture created by a 3D Morphable Model-based technique [13]. The key methods and advancements in 3D face reconstruction using 3D morphable face model (3DMM) during the past 20 years are examined in this study. It includes the advantages and limitations of various approaches, and their practical applications [14]. A technique has been developed to create 3D representations of faces using only one photograph and a 3D model of another person face as a reference. The approach capitalizes on the similarities in facial structure among individuals and modifies the reference model to resemble the desired face [15]. Face recognition normally comprises two steps, face detection, and face identification, as was demonstrated in this study [16]. Deep learning is highly accurate in facial recognition. A study gathered data from 518 online questionnaires to explore the factors influencing facial recognition usage. The study found that convenience does not significantly affect usage frequency, but perceived benefits have a positive impact. These findings contribute to understanding and promoting the beneficial use of face recognition while protecting privacy [17]. This study utilized three popular machine learning techniques (Decision Tree, K Nearest Neighbor (KNN), and Support Vector Machine (SVM)) and three sets of facial image data to evaluate their proposed identification method. The recommended approach outperforms the comparative algorithms in terms of recall, precision, accuracy, and specificity [18].

The most recent advancements in face recognition using deep learning in biometrics are the main topic [19]. It will discuss how deep learning is used in face recognition technology, its applications, and an analysis of deep learning techniques, ideas, and methodology. The development of a remote attendance system by combining a facial recognition system with a server has been proposed, and it employs the Raspberry Pi, a cost-effective and energy-efficient device, to implement the face recognition system [20]. The project discussed in this paper focuses on integrating face processing functionality into the Mimer SQL database, aiming to enhance its competitiveness and versatility [21]. The integration project will be implemented across multiple platforms, namely Windows, Windows CE, and Linux. Additionally, the FMG organization has developed a tool known as the Missing Person Intelligence Synthesis Toolkit (MIST), which utilizes a data-driven approach to search for missing individuals [22]. This article delves into the origins, methods, and applications of algorithms, examining their performance in terms of robustness, accuracy, and reliability [23]. The specific application discussed in this context enables users to upload complaints, which are then stored on a web server accessible to trusted members through the application. To optimize the search operation in terms of precision and speed, the system incorporates four key components: User, Police, Complaint holder, and Admin [24]. The use of hybrid deep learning techniques [25]–[27] and recurrent neural networks [28] can be explored to enhance the accuracy of the models. This approach can potentially improve the predictions and enables us to make more informed decisions. In an uncontrolled setting with low- resolution photos taken from moving cameras at the Al Nabvi mosque in Madinah, a study offered a unique integration of face recognition algorithms with a soft voting mechanism to identify missing people in scenarios with big crowds. [29].

A comprehensive overview of recent advancements in low-density parity-check (LDPC) decoding algorithms for reliable data transmission and reception has been provided, which highlights the significance of information theory coding in solving secure data communication problems and discusses the growing utilization of LDPC code-based decoding algorithms [30]. A study focuses on the development of a hybrid model that combines deep learning and classical machine learning techniques for face mask detection. The model consists of two main components: feature extraction using Resnet50 and classification using decision trees, Support Vector Machine (SVM), and ensemble algorithms. The researchers investigated three different datasets: Real-World Masked Face Dataset

(RMFD), Simulated Masked Face Dataset (SMFD), and Labeled Faces in the Wild (LFW) [31].

III. Methodology

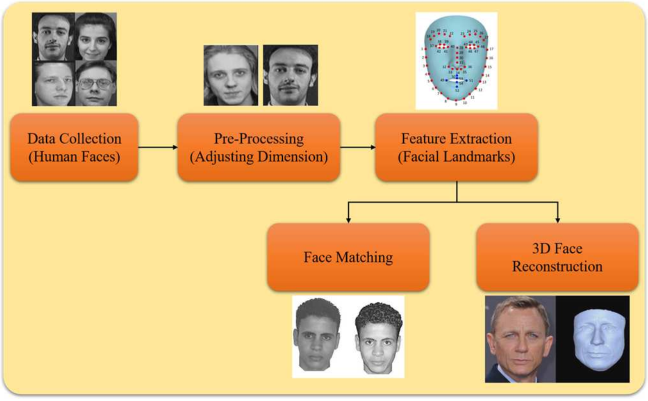


Fig. 2. Framework for proposed methodology

A. Dataset

In this research, as mentioned in Fig. 2, the first step is data collection, and the study utilized two widely recognized datasets in the field of computer vision. The first was the ORL dataset, which is commonly used for matching faces, while the second was the 300-W dataset, which is often employed for reconstructing three-dimensional faces. The ORL dataset, also known as the Olivetti Research Laboratory database [32], is a set of 400 grayscale photographs of 40 people, with ten photographs of each person being included. The photographs were all taken under various lighting settings. With its wide range of facial variations and lighting situations, this dataset has established itself as a gold standard in face recognition research. By incorporating the ORL dataset, the algorithms developed in this study can be thoroughly evaluated in terms of their face-matching performance. On the other hand, the 300-W dataset is a comprehensive benchmark for 3D face reconstruction [33]. The 300-W is a human face dataset made up of 300 photos taken in-the-wild inside and outdoors. It encompasses a wide range of identity, expression, lighting, stance, occlusion, and face size. By conducting searches on search on google for terms like "football", "conference", "celebrities", "party", and "protests" the photographs were retrieved. The 300-W database has more partially-occluded photos than any of the other in-the-wild data do, and it also includes expressions other than "neutral" and "smile" such as "surprise" and "scream". Using a partially automatic process, 68-point markup was added to images.

B. Pre-processing

Before face matching using the ORL dataset, the images were preprocessed to have a resolution of 92 × 112 pixels and 256 shades of grey per pixel. To ensure precise facial landmark identification, which is essential for successful face recognition, this resolution was chosen. After that, each image's annotation of the facial landmarks served as a means of standardizing and aligning the images in preparation for further analysis. Similar preprocessing was done on the 300-W dataset for face reconstruction to ensure uniform size and quality. This involved matching the annotated facial landmarks and shrinking the photos to a standard size, usually 256 × 256 pixels. This phase is crucial to make sure that each face's features are in a uniform place, enabling more precise comparisons between photos. The outcomes of the algorithms may be more easily compared and evaluated the datasets, resulting in a more thorough examination of their performance.

C. Feature Extraction

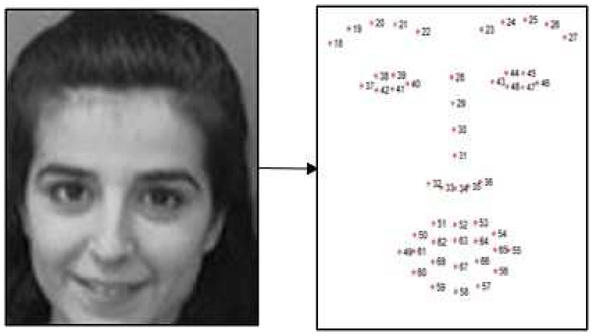


Fig. 3. Facial landmarks for an image

As shown in Fig. 3, facial landmarks were extracted from the preprocessed images using the Dlib package. Following their extraction, these landmarks served as features for face matching in [34]. By default, the Dlib software can extract 68 face landmarks. The corners of the lips, the outer borders of the brows, the tip of the nose, and other distinctive facial features are represented by these landmarks. The face-matching algorithm was then used with the acquired facial landmarks as inputs to successfully match the faces for fresh human faces. In the realm of face recognition, this strategy to feature extraction has been found to be quite effective in prior studies [35]. The model [36] will be trained using features from the 300-W dataset, which provides facial landmarks for 3D human faces. Facial landmarks are used as features in both datasets in this method, which creates a robust and distinctive representation of the face that makes accurate face matching and reconstruction possible.

D. Model Building

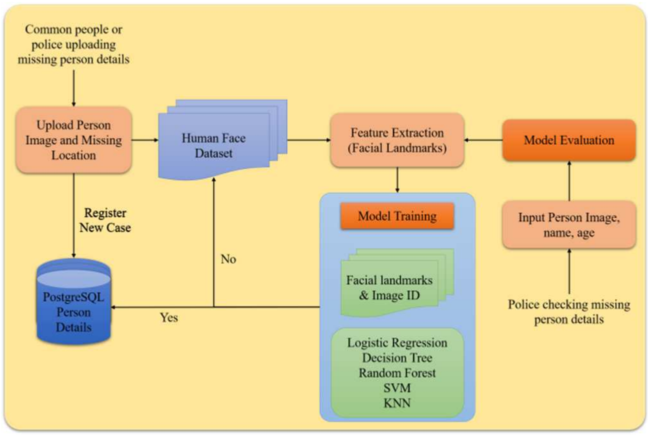


Fig. 4. Flowchart for face matching

A face-matching system was proposed in this study, as depicted in Fig. 4, that trains machine-learning models on facial landmarks. These landmarks capture distinctive features that can help in face matching and offer crucial information about the geometric structure of the face. By focusing on the critical facial features that are needed for precise identification, the system may concentrate on the characteristics that are most important to the face: the landmarks. Five machine-learning techniques were chosen to train the face-matching models:

1) Logistic Regression:

A well-liked classification approach called logistic regression models the association be- tween input features and binary outputs. It is appropriate for face matching since it can calculate the likelihood of a match using the provided facial traits.

2) Support Vector Machine (SVM):

Another classification algorithm that uses hyperplanes to divide data points into various classes is SVM. It is particularly effective when dealing with high-dimensional data like facial landmarks.

3) Decision Tree:

Decision Tree algorithms create a tree- like model to make decisions based on feature values. They are well-suited for face matching as they can handle both categorical and numerical features, making them capable of capturing complex relationships between facial landmarks and matching identities.

4) Random Forest:

An ensemble learning technique called Random Forest uses several decision trees to produce pre- dictions. It is advantageous for face matching as it reduces overfitting and improves the overall accuracy of the system by averaging the predictions of multiple trees.

5) K-Nearest Neighbor (KNN):

A non-parametric classification algorithm called KNN assigns labels based on the feature space's nearest neighbors. In face matching, KNN can determine the similarity between facial landmarks and match identities based on the proximity of feature vectors.

These models were trained to establish a correlation be- tween facial features of human faces and accurately identify individuals based on probability scores. To achieve robust and accurate outcomes, the models underwent extensive training using a comprehensive dataset consisting of facial features and corresponding identities. A threshold of 75% was established as the minimum probability score required to classify a face match as successful. If the generated probability score exceeded 75%, the face has deemed a match; otherwise, it was categorized as a non-match. Subsequently, the trained models were employed for face matching on test images to assess the system performance.

E. 3D Face Reconstruction

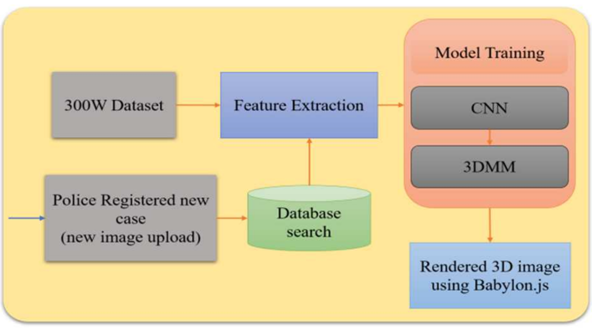


Fig. 5. Pipeline for 3D face reconstruction

The pipeline for 3D face reconstruction is illustrated in Fig. 5, and CNNs architecture is illustrated in Fig. 6, are comparable. By using images from the 300-W dataset, the CNN model was trained on preprocessed images to establish a connection between the 2D landmarks and the 3D facial structure [37]. Through a series of convolutional and pooling layers, the CNN learns to extract relevant features from the input images, enabling it to capture the complex relationship between 2D facial appearance and 3D facial structure. The output of the CNN is a set of parameters or coefficients that effectively represent the 3D shape of the face.

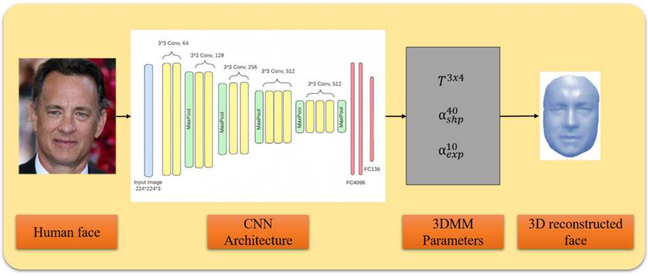


Fig. 6. Architecture of 3D Face reconstruction Model

A 2D facial image is fed into the trained CNN during the reconstruction process, and it extracts the associated 3D form coefficients. The 3DMM is then employed with these coefficients to produce a rebuilt 3D face form that most closely resembles the calculated coefficients. Based on the data in the 2D image, this approach enables the estimation of the face underlying 3D structure. Finally, a rendering engine like Baby- lon.js is used to visualize the recreated 3D face shape. In this step, the reconstructed face is rendered and visualized, making it easier to visually evaluate and analyze the reconstructed facial characteristics and structure. The optimization function used to enhance the CNN was Mean Squared Error (MSE), which gauges the variance between the 3D shapes that were predicted and those that were actually there.

IV. RESULTS & DISCUSSION

This study assessed the effectiveness of SVM, Logistic Regression, Random Forest, Decision Tree, and KNN, among other machine learning techniques for face matching. A thresh- old of 75% likelihood was established for face matching, and any score below this threshold was viewed as an error.

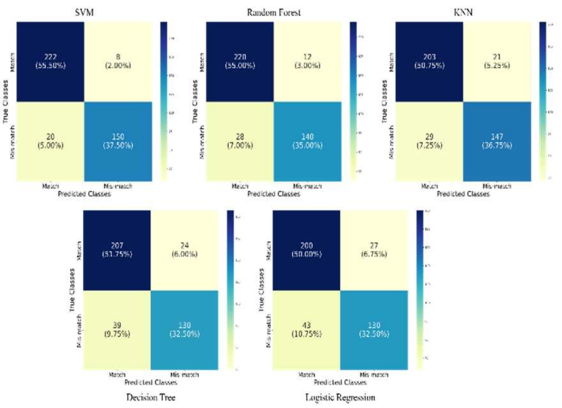
A. Confusion Matrix

A confusion matrix Fig. 7(a), which classifies the accuracy of facial image classifications, was made using a collection of 400 photos. The precision (eq. 1), recall (eq. 2), and accuracy (eq. 3) equations, where TN = True negative, TP = True positive, FN = False negative, FP = False positive, are used to assess the effectiveness of the model by quantifying its accuracy in correctly classifying data and locating relevant information. When a facial image is correctly recognized as matching a reference image, a true positive is noted. When a non-matching face image is mistakenly identified as a match to a reference image, a false positive is produced. When a non-matching facial image is successfully identified as being unrelated to a reference image, it is said to be a true negative. When a similar facial image is wrongly identified as being unrelated to a reference image, it is referred to as a false negative. The accuracy and efficiency of facial matching and 3D face reconstruction procedures are evaluated using evaluation metrics, which are extremely important. Accuracy, precision, and recall were the metrics used in this study, as indicated in Table-I. These metrics offer quantitative measurements that make it possible to evaluate the suggested methods thoroughly.

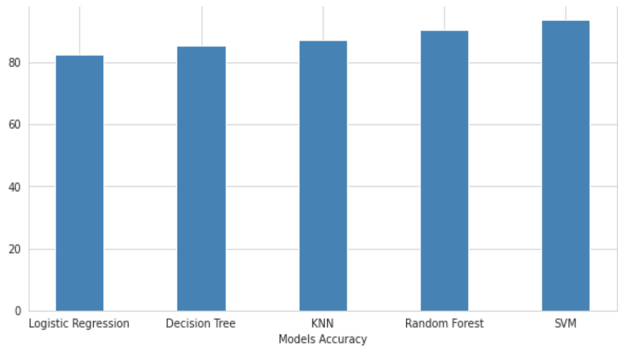
$$Precision = \frac{T_p}{T_p + F_p} \tag{1}$$

$$Recall = \frac{T_p}{T_p + F_N} \tag{2}$$

$$Accuracy = \frac{T_p + T_N}{T_p + F_p + T_N + F_N} \tag{3}$$



(a)



(b)

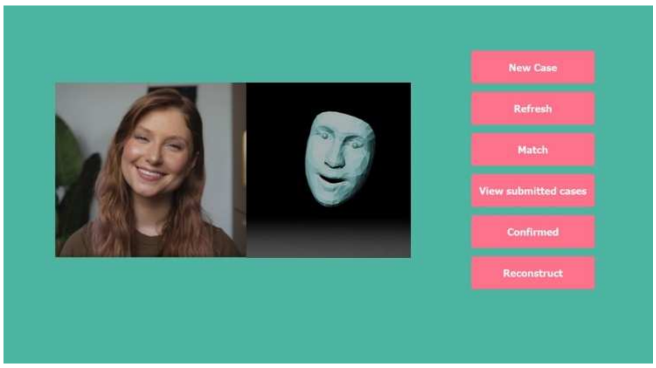
Fig. 7. (a) Confusion matrices for different Classifiers (b) Comparison of accuracy for different Classifiers

The performance of various algorithms was assessed using accuracy, precision, and recall measures. The findings indicate that SVM had the highest accuracy rate of 93.79%, followed by Random Forest, which had an average validation accuracy of 90.38%. The other algorithms performed well, with KNN achieving 87.15% accuracy, Decision Tree achieving 85.50% accuracy, and Logistic Regression achieving 82.65% accuracy, as illustrated in Fig. 7(b). When compared to the existing models [38], the models in this study achieved precision rates of 90% for KNN, 59% for SVM with Principal Component Analysis (PCA), and 43% for SVM. The SVM algorithm excels in finding optimal hyperplanes to separate classes in high-dimensional feature spaces. Its suitability for face recognition has been demonstrated in several studies, where SVM achieved high accuracy rates [39], [40]. In this work, the superior performance of SVM can be seen Fig. 7(b). In comparison to other models like Random Forest, SVM offers advantages such as better generalization and robustness, especially in scenarios with limited samples or high-dimensional data. While Random Forest has been utilized in face recognition, the majority of research favors SVM for its superior accuracy and ability to handle complex facial matching problems. It should be noted that the choice between SVM and Random Forest may depend on specific dataset characteristics and computational resources. Overall, SVM emerges as a compelling choice for face matching, supported by its proven effectiveness and ability to handle high-dimensional data.

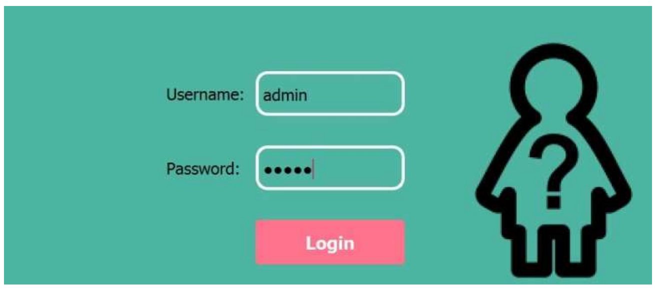
TABLE I. COMPARISON OF DIFFERENT PERFORMANCE METRICS

Model	Precision	Recall	Accuracy
Logistic Regression	83.33%	86.95%	82.65%
Decision Tree	84.27%	91.26%	85.50%
KNN	88.21%	91.56%	87.15%
Random Forest	88.70%	94.82%	90.38%
SVM	**91.80%**	**96.55%**	**93.79%**

The user interface for face reconstruction that is designed for ease of use and simplicity is illustrated in Fig. 8(a), and Fig. 8(b) shows the login window, which is a crucial component of any secure application. To access the application, the user must enter their credentials, such as their login and password, into the window. Clear directions on how to enter the necessary information are provided on the interface, which is made to be easy and user-friendly.



(a)



(b)

Fig. 8. (a) User Interface for Face Reconstruction of an Image (b) User Interface for Login

The face reconstruction model achieved a high accuracy of 90%, indicating the success of accurately predicting 3D models of 2D face images in the approach. The reduction of false positives and false negatives, along with high precision and recall scores, further affirm the models effectiveness. To visualize the predicted 3D model, a standard 3D graphics library was utilized. The produced model's exhibited high quality, featuring smooth surfaces and distinct facial features, thereby demonstrating the efficacy of the technique in extracting the underlying 3D geometry from the 2D input image.

The results of the study demonstrate that SVM and Random Forest models are effective in accurately predicting face matches using machine learning. SVM has the highest accuracy, demonstrating its reliability as a face matching model. The accuracy gap between SVM and Random Forest, however, was barely noticeable. Notably, accuracy ratings of more than 80% were achieved by the KNN, Decision Tree, and Logistic Regression models. These models may be useful in situations where computational effectiveness is a top priority because they use less computing power than SVM and Random Forest. The outcomes also demonstrate the great accuracy attained when CNN was used to recreate 3D faces from 2D photographs, demonstrating its potential as a useful tool for a variety of applications.

It is crucial to recognize the restrictions placed on the research used in this study. The model's potential bias in accuracy when applied to various demographic groupings is a significant drawback. The performance of the model may be affected by differences in facial characteristics and skin tones among people from various racial and ethnic origins. Further evaluation and testing across a broader range of populations are necessary to ensure fairness and unbiased results.

V. CONCLUSION & FUTURE WORK

This study highlights the effectiveness of machine learning algorithms in face matching. The findings suggest that SVM and Random Forest are the most effective models for this task, achieving high accuracy scores. The method for 3D face reconstruction using CNN after training the models with 2D facial landmarks and 3D face models has demonstrated promising results. The model achieved a high accuracy of 90%, and the visualizations of the predicted 3D models exhibited good quality.

Future research directions in facial matching and reconstruction using deep learning hold great potential for advancing the field. To enhance precision, exploring advanced loss functions and attention mechanisms can optimize the model's ability to differentiate between similar faces and improve matching accuracy. Improving training data quality by collecting diverse and representative datasets, addressing biases, and employing data augmentation techniques can contribute to more robust models. Additionally, exploring alternative architectural models, such as recurrent neural networks or transformer-based models, can lead to further improvements in accuracy and efficiency. Testing the models on diverse datasets incorporating variations in lighting, image quality, and demographic representation will ensure their robustness and generalizability. These research directions pave the way for more accurate and reliable facial matching and reconstruction techniques, advancing the identification of missing persons and related applications.

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