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RESEARCH ARTICLE

2D-3D Facial Image Analysis for Identification of Facial Features Using Machine Learning Algorithms With Hyper-Parameter Optimization for Forensics Applications

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ABSTRACT Recognizing a face is a remarkable process that humans naturally use. Computer vision has tried to resemble this ability of human vision as a biometric tool to identify humans. Commercial and law enforcement applications are increasingly using face recognition technology to identify people. Currently, it is one of the most sought-after detection methods used in forensics for criminal identification purposes. Owing to similarities in the appearance of certain faces, especially in criminal cases, this problem poses a great challenge in forensic investigation and detection. The novelty of this work lies in the development of a framework for face recognition using 2D facial images gathered from various sources to generate a 3D face mesh using 468 MediaPipe landmarks which detects multiple faces in real-time. This leads to the generation of input feature vectors being formulated utilizing Euclidean/Geodesic distances and their ratios between the landmarks. These feature vectors are then trained into various classifiers that can provide the correct matching decision in an unrestricted environment such as large pose, expression, and occlusion variations. These quantitative similarity measures can then be presented as statistical evidence to identify criminals in forensic investigations. This two-dimensional to three-dimensional annotation provides a higher quality of three-dimensional reconstructed face models without the need for any additional three-dimensional morphable models. The proposed methods were validated and tested to achieve comparable recognition performance using hyperparameter optimization. Regarding accuracy, the statistical results show that Extreme gradient boosting is the best classification model that provides the best accuracy (78%) for predicting facial images compared with Adaptive Boosting (77%), Random Forest (75%), Bernoulli Naive Bayes (68%), Decision Tree (57%), Logistic Regression (71%), Light Gradient Boosting Model (58%), Extra Tree Classifier (57%), Support Vector Machine (58%), and Nearest Centroid (62%) classifiers which can be further increased by considering a greater number of images in the dataset implying at the potential of further research for scale-up implementation.

INDEX TERMS Face detection, 468 landmark detection, Euclidean distance, geodesic distance, classification, machine learning in criminalistics, forensic.

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ABBREVIATIONS AND ACRONYMS

FRS Face Recognition System.
2D Two Dimensional.

3D	Three Dimensional.
SVM	Support Vector Machine.
ANN	Artificial Neural Network.
KNN	K-Nearest Neighbor.
DT	Decision Trees.
XGBoost	eXtreme Gradient Boosting.
AdaBoost	Adaptive Boosting.
MTCNN	Multi-Task Cascaded Convolutional Networks.
DLIB	Digital Library.
ROC	Receiver Operating Characteristic.
FAR	False Accept Rate.
FRR	False Reject Rate.
TAR	True Accept Rate.
TAR	False Reject Rate.

I. INTRODUCTION

Biometric imprints are based on the understanding that each person is unique. The face is the most important factor in defining physical attractiveness. Humans can recognize each face's unique imprint based on its distinguishing traits. Face recognition examines the capability of human vision to measure faces for identification. As a result, there has been a lot of focus on designing algorithms that mimic the human vision process for face recognition. When other biometric modalities are unavailable, facial recognition, a type of biometric identification, is employed. Face capture, which is both natural and non-intrusive, has been shown to be one of the most effective biometrics for face recognition. With no definitive results, computer vision has attempted to mimic the capabilities of the human eye. However, face recognition appears to be a valuable and practical technology forensic examiners employ in criminal investigations [1], [2].

Face recognition is a popular scientific approach with a wide range of applications; however, it is prone to several problems. The challenges identified are automated face detection, recognition of face images such as identical twins and look-alikes, facial aging, occlusion, expression, and pose variation effects, illumination conditions, low resolution, quantitative and qualitative methods for setting parameters and estimating characteristics of the face, seeking solutions through digital anthropometry and other challenges [3], [4], [5], [6], [7], [8], [9], [10], [11]. Despite increased law enforcement, criminal offenses appear to be perpetrated at a high rate by people with similar faces, particularly identical twins [12], [13], [14], [15], [16]. According to a recent study, the face recognition system does not work as well in the case of identical twins as in the case of other people. Consequently, erroneous identification must be avoided to prevent the accidental conviction of an innocent individual. The identification of similar or similar-looking faces is difficult; therefore, there is significant motivation to pursue their recognition. The current facial recognition system failed to distinguish identical twins. In addition, deep neural networks face the same challenge of distinguishing between similar faces, such as identical twins, and look-alikes. Over the years, many approaches have been proposed using several recently developed and well-performing algorithms and databases, considering both favorable and unfavorable situations; however, these have been unsuccessful. Consequently, the primary goal of the proposed research is to accurately determine criminal identification in forensics-related fraud and crime.

Although in the past, pursued progress has been made focusing on 2D face images, it still has drawbacks with regard to limitations in performance due to factors such as variation in head pose, expression, occlusion, illumination, etc. To overcome these limitations, researchers have focused on 3D face recognition technology which has the advantage of obtaining more geometric information about the face such as face margin curves, curvature characteristics, and geodesic distances, which could substantially improve accuracy. The main drawback of 3D model-based approaches is their inability to store large data files, which is computationally costly and not applicable to real-life face recognition systems [17], [18], [19], [20], [21]. The research community has provided a third solution that suggests a combination of 2D and 3D modalities [22], [23], [24], [25]. This approach appears to be a reasonable solution that can overcome the limitations of improving each system.

Similarity measures of 3D facial surface have become hot topics, that have important applications in face recognition, 3D facial reconstruction, facial surgery, 3D animation, biometrics, forensics, and other fields. The similarity between two objects is often different when judged by different people, depending on the perception and experiences of each person. Therefore, similarity measurement is difficult. In particular, human face similarity is more difficult to measure because human faces are globally similar in terms of their main physical features (eyes, mouth, nose, etc.) Remarkable approaches with the best algorithms and databases have been presented over the years, considering the favorable and unfavorable situations to study face recognition, and have been found unsuccessful in matching up to expectations. With the increased birth rate of twins, which is the cause of fraud and a growing crime rate, there is an urgent need to integrate the existing automated face recognition system with the forensic face recognition method, which has the immense liability to follow legal procedures.

The main goal of the framework proposed in this paper is to recognize faces by employing 2D images of faces to approximate a 3D face mesh using 468 landmarks of media pipe framework, along with features extracted through Euclidean and geodesic distances between these landmarks, as well as utilizing different classifiers for the images collected from the web that can provide the correct matching decision in an unrestricted environment. This paper proposes a new data set for checking facial image comparison. Face detection, pre-processing, landmark detection, feature extraction, identification, and authentication were performed as part of this study. Face landmark extraction must be quick and accurate to meet the demands of various capabilities, such as real-time processing or mobile device rendering [26], [27], [28], [29]. Precise recognition of landmarks is performed using Mediapipe [31], [32], [33], [34], [35] which is mainly used in real-time applications such as emotion detection, Parkinson's disease detection, driver drowsiness detection, and early-stage autism screening [36], [37], [38], [39], [40], [41]. It estimates 468 landmarks in real-time to improve the accuracy of the face recognition system (FRS) compared to other existing approaches, such as Multi-Task Cascaded Convolutional Networks (MTCNN) [42], [43] and Digital Library (DLIB) [44], [45]. After that, Euclidean and Geodesic distances were measured from the selected landmark points to extract the features. The quantitative similarity measures are then given as inputs to various classifiers such as Extreme gradient boosting (XGBoost), Adaptive Boosting (AdaBoost) classifiers, Random Forest (RF) classifiers, Bernoulli Naive Bayes (NB), Decision Tree (DT), Logistic Regression (LR), Light Gradient Boosting Model(LGBM), Extra Tree Classifier(ETC), Support Vector Machine (SVM), and Nearest Centroid (NC) classifiers to identify criminals in the forensic investigation by presenting them as statistical evidence. This study explores the forensic aspects and applications of a biometric face recognition system.

The Contributions in the paper are listed below.

1) There is an impending need to blend the manual approach of analyzing biometric images using anthropometric and morphometric-based measurements to generate evidence based on expert opinions with the Artificial Intelligence/Machine Learning approach to provide effective evidence. Therefore, the proposed approach generates significant features that can be used in real-world forensic applications.
2) The correct matching decision under varying facial expressions and pose variations in an unconstrained environment can be obtained in the proposed method.
3) A framework for recognizing faces involved in crime and fraud and supporting a criminal investigation by forensic science experts is possible.

A. PAPER ORGANIZATION

The rest of the paper is organized as follows: Section II explains the related work on the methods used. Section III describes the research methods adopted for facial image analysis to identify facial features using machine learning algorithms. The results are presented in Section IV. Section V concludes the paper and discusses future work.

II. LITERATURE SURVEY AND RELATED WORK

A. BACKGROUND THEORY

The standard view among face recognition researchers is that determining the resemblance between faces, particularly in cases of look-alikes in criminal investigations, is the most demanding and challenging. Biometric prints generated from the faces of look-alikes, particularly identical twins, have been found to be remarkably similar. Over the years, remarkable approaches using the best algorithms and databases have been presented to explore face recognition in both favorable and unfavorable situations, but have been found to fall short of expectations [3], [6], [9], [10], [12], [13]. With the increased birth rate of people with similar facial features, there is greater urgency and need to integrate existing automated face recognition systems with forensic face identification methods, which have a high level of legal liability. This may reduce fraud and increase crime rates by considering the source features.

1) DIGITAL FACIAL ANTHROPOMETRY

Physical anthropology at the end of the 13th century was initiated as descriptive and comparative science also known as forensic science by the Italian merchant Marco Polo (1254–1324). In the 18th century, Alphonse Bertillon, a French police officer, and a bio-metrics researcher (1853–1914) developed a breakthrough system for criminal identification based on the anthropological technique of anthropometry, on which the facial recognition system was built. Anthropometry is the scientific study of the measurement and proportions of the human body. Morphometry is a branch of mathematics that deals with the quantitative analysis of size and shape. It is a combination of geometry and biology that deals with the study of shapes in two or three dimensions, respectively. Qualitative and quantitative features were used to describe human faces. Anthropometric measurements involve the identification of certain points on a subject's face, called landmark points. Facial landmark extraction is the process of plotting face key landmarks representing important regions of the face such as the tip of the nose, center of the eye, etc. of an image. It allows for identifying the shape and orientation of the face, as well as extracting facial features [48].

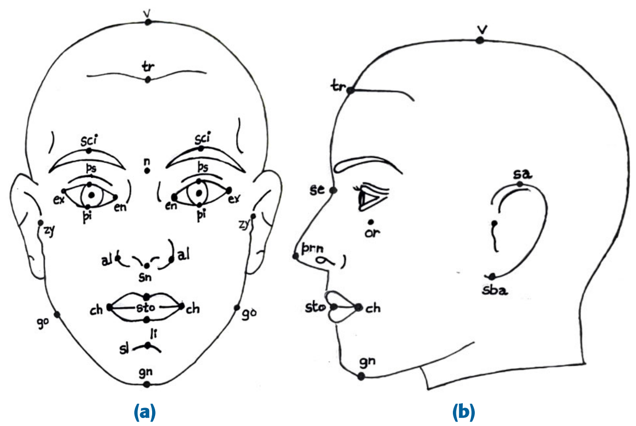

FIGURE 1. Representation of anthropometric landmark points on (a) Frontal facial image and (b) Side posture of the face [9].

Figures 1 and 2 depict sample anthropometric reference points, their definitions, and different distances applied in our suggested method for face recognition. Figure 1 shows anthropometric reference points for the frontal facial

TABLE 1. The anthropometrical landmarks of the face along with their descriptions [9].

Anthropometrical Landmarks	Definition
Vertex (v)	The highest point on the head
Trichion (tr)	Anterior hairline at the mid-line
Glabella (g)	The most prominent mid-line between eyebrows
Nasion (n)	The midpoint on the soft tissue contour of the base of the nasal root
Exocanthion (ex)	The soft tissue point located at the outer commissure of eye fissure
Endocanthion (en)	The soft tissue point located at the inner commissure of eye fissure
Palpebralesuperius (ps)	The highest point in the midportion of the free margin of each upper eyelid.
Palpebraleinferius (pi)	The lowest point in the midportion of the free the margin of each lower eyelid.
Orbitale (or)	The lowest point on the margin of the orbit. The orbit is the bony cavity that contains the eyeball
Superaurle (sa)	The highest point of the free margin of the auricle.
Subaurale (sba)	The lowest point on the free margin of the ear lobe
Subnasale (sn)	Junction of the inferior portion of the nasal septum and the upper lip
Sellion (se)	The most posterior point of the frontonasal soft tissue contour in the midline of the base of the nasal root
Pronasale (prn)	The most anterior midpoint of the nasal tip
Alare (al)	The most lateral point on each nostril contour
Labiale inferius (li)	the midpoint of the vermilion border of the lower lip
Labiale superius (ls)	the midpoint of the vermilion border of the upper lip.
Cheilion (ch)	The point of the mouth corner
Stomion (sto)	The midpoint of the labial commissure when the lips are closed.
Gnathion (gn)	The lowest median landmark on the lower border of the mandible
Gonion (go)	The most lateral point at the angle of the mandible.
Pogonion (pg)	The most anterior midpoint of the chin

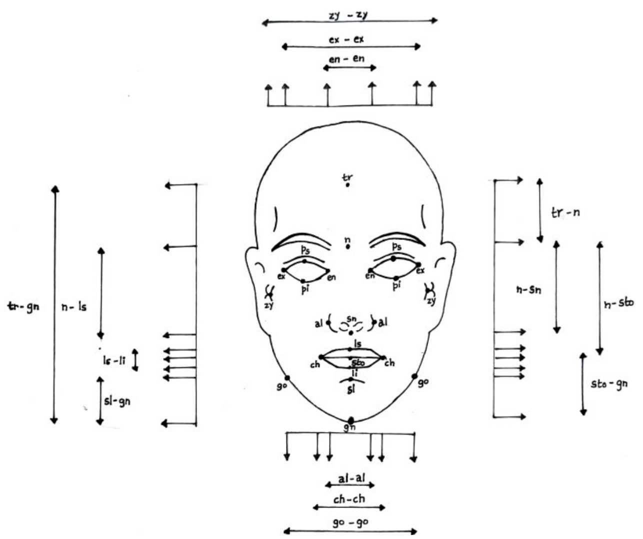

FIGURE 2. Measurements of distances between various anthropometric landmarks.

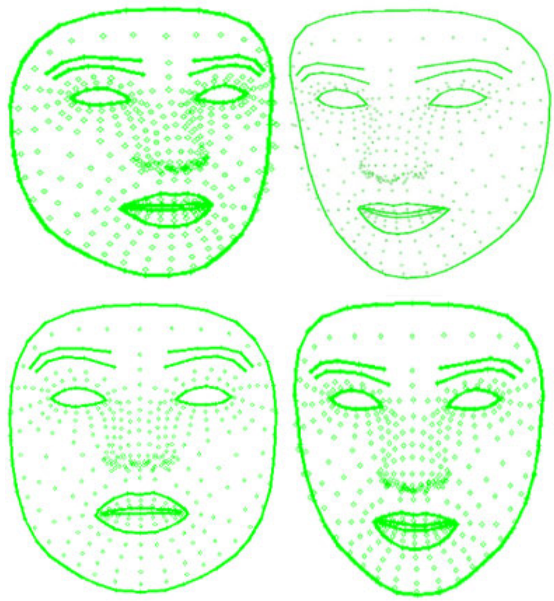

FIGURE 3. Representation of 468 face landmarks for a frontal image and images with different poses in three-dimensional space using Mediapipe framework.

image(a) and the side posture of the face(b). Table 1 lists the anthropometrical landmarks of the face along with their descriptions.

Figure 2 shows the process of measuring various distances, such as the Euclidean Distance (ED) and Geodesic Distance (GD). Example: Distance between Alare and Alare (nose width), Cheilion to Cheilion (mouth width), exocanthian to chelion (upper cheek height), nasion to sub nasale (nose height), sub nasale to chelion (upper lip length), sub nasale to gnathion(lower facial height), and stomion to labiale infirious (vermilion height of the lower lip) using the extracted pair of landmark points. By using these measured distances different facial ratios such as Inter canthal width to Bizygomatic breadth, Mouth breadth to Mouth width Vermilion height of the upper lip to Vermilion height of the lower lip, can be obtained.

In the proposed approach, after detecting the face position in an image, the next step is to locate 468 landmarks using a media pipe [30], [31], [32], [33], [34]. Mediapipe is an open-source framework for ‘‘building world-class machine learning solutions’’ using Google which is fast and highly accurate [31], [35], [36], [37], [38], [39], [40], [41]. 2D facial images are used to detect 3D face meshes (which include

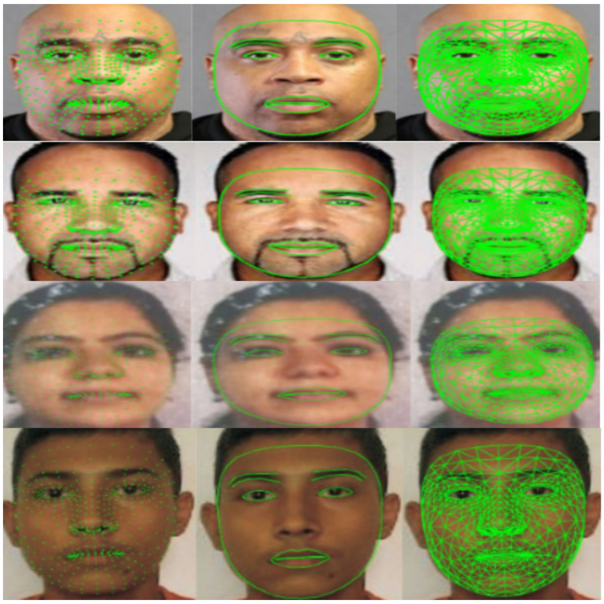

FIGURE 4. Overlaying of 468 landmarks on facial images [60], [61], [62], [63] of the self-created dataset and face mesh generation from the extracted landmarks.

468 facial landmarks with 3D space coordinates) by employing the media pipe framework which works well for varying lighting conditions, occluded faces, and faces of various sizes and orientations in real-time. More information is derived from the facial mesh topology than is needed, which also makes it possible to select only the necessary information.

A total of 468 landmarks were acquired for the facial images with different poses as important features which are shown in Figure 3. Figure 4 shows the result of generating 468 landmarks, overlaying 468 landmarks on facial images of the self-created dataset, and generating face mesh with different poses from the extracted 468 face landmarks.

B. LITERATURE REVIEW RELATED TO ANTHROPOMETRIC FEATURE-BASED FACIAL IMAGE ANALYSIS IN 2D AND 3D FOR FACE RECOGNITION

Sudhakar and Nithyanandam [8] focused on a fusion-centered method for identifying identical twins. The features extracted using Histogram Oriented of Gradients (HOG), PCA, Gabor distance between the facial components, and local binary pattern (LBP) were combined in this study. The twins were identified using fusion-generated scores in this method. The best feature was selected by using Particle Swarm Optimization, and an SVM classifier was used to train and test the image. Better outcomes with high accuracy and less processing time were obtained using this approach compared with the prevailing methodologies. However, images with various expressions and poses were considered, and realistic images were not considered for evaluation.

Kukharev and Kaziyeva [9] presented a review that included a brief history of anthropometry and its evolution into modern methods and approaches using computer science for facial anthropometry, issues on morphometry, qualitative and quantitative methods for setting parameters and estimating characteristics of the face, distinctive cases in the recognition of face images such as identical twins and look-alikes, and various solutions through digital anthropometry.

Moung [10] reviewed solutions using state-of-the-art techniques to address the challenges faced in face recognition. The identified challenges are (i) automated detection of the face (ii) angle of face poses (iii) effects due to occlusion (iv) various facial expressions (v) face aging, (vi) different light conditions, (vii) low-resolution images, (viii) similarity in twins and faces that look alike, and (ix) other technical challenges. To authenticate identical twins in addition to the face recognition biometric system, other biometrics have been proposed.

Nassih et al. [11] presented an FRS based on 3D, using "Geodesic Distance" - GD measured using Riemannian geometry and "Random Forest"-RF. Subsequently, to solve the Eikonal equation, the algorithm named "Fast Marching-FM" measures distances geodesically between a set pair of points of 3D faces, thus naming it GDFM+ RF. To analyze class separability, "Principal Component Analysis"-(PCA) was employed on the extracted features drawn from the geodesic facial curves. The extracted features are then applied to the "RF" classifier as the input feed. The authors suggested that to investigate the method's effectiveness, instead of "Fast Marching," it is best to use any other algorithm to compute the geodesic distances.

Afaneh et al. [46] used a two-level decision method to propose a system for recognizing identical twins. They applied score-level, feature-level, and decision-level fusion; to improve accuracy, a CNN was employed in the recognition process. Feature extractors such as PCA, LBP, and HOG were used in this study for the standard FERET datasets and ND TWINS- 2009-2010. The experiments proved that compared to unimodal systems, the multimodal biometric system improved recognition performance. For identical twin recognition, the Equal Error Rate obtained for the Controlled Illumination Condition was 2.2 (%), and that for the neutral expression was 2.7 (%).

Mousavi et al. [7] suggested a Modified SIFT (M-SIFT) algorithm along with crowdsourcing to distinguish the similar faces of identical twins. The eyebrows, eyes, nose, mouth, and face curves are the five regions in which the face in each image is partitioned. Among the facial five regions, these approaches ascertained that the face curve was the most significant facial feature for discriminating between identical twins. A total of 650 images were obtained from 115 pairs of identical twins and 120 non-identical twins using this method. The experiential outcomes showed that 7.8%, 8.1%, and 10.1% had the lowest Equal Error Rate (EER) of identical twin recognition for the entire image, only frontal images and PAN motion images, respectively. However, landmark regions cannot be detected using the face region landmarks detection (FRLD) algorithm.

Nafees and Uddin [47] presented a gray-level co-occurrence matrix that measured the texture of images to predict twins. To match the initial stage, the best criteria are identified using the histogram and RGB colors in this framework. The security vulnerabilities associated with twin-face identification and detection were prevented using the proposed method. Diverse twin datasets were used to test this methodology. When analogized with other methodologies for the prediction of twins better performance was attained by the presented method with good accuracy. This approach can also be applied under controlled circumstances that are adaptable to a wide range of facial variations. However, this method requires a long processing time.

Jasbir et al. [48] used traditional feature-based approaches (angular and linear) handcrafted by researchers to calculate the measurements using landmarks. This approach has been used to study sex and ethnicity, thereby confirming its success. This approach verified for the first time that facial anthropometric measurements could be employed on 2D data sets developed through computer science. Thus, computer science researchers have been motivated to study facial anthropometry.

Rachid [49] presented two feature extraction methods to achieve a 2D face recognition system using detected facial feature points, thereby computing between points to measure their distances using "Geodesic Distance" - GD and "Euclidean Distance"-ED, as in Riemannian geometry and Euclidean geometry, respectively. These measured distances were then used as inputs for various classification algorithms, and the results revealed that computing "GD" for extracting image features is more efficient than using "ED".

C. LITERATURE REVIEW RELATED TO FACE RECOGNITION USING MACHINE LEARNING ALGORITHMS

Shi et al. [50] proposed an approach that combined LBP and SVM to develop a system for 3D face recognition. The authors used the LBP algorithm and SVM classifiers for feature extraction and classification, respectively. The results prove that the algorithm requires less time, improves accuracy, is less complex, and is faster.

The Transfer Learning (TL) method was utilized by Nahar et al. [51]. Geometric and photometric characteristics were used. Two VGG16-trained networks are considered. The combination of geometrical and photometric features yielded 98 percent accuracy. Therefore, there is a need for more identical twin imaging data. Google Data includes four pairs of twins, each with 17 different positions; the photometric characteristics provide 96 percent accuracy. Existing modalities, such as palm print, face, voice, and others, can be used with other transfer learning methods.

Ahmad et al. [52] proposed a deep neural network to identify identical twins. Using triplet loss, they employed two alternative CNN models. The best accuracy attained was 87.20 percent, which shows that identical twin faces are a very difficult challenge for strong, deep networks.

Khawla et al. [53], [54] presented a deep learning-based facial recognition attendance system. SqueezeNet, GoogleNet, and AlexNet were the three networks used. Similar and veiled faces are not recognized using this technology. To improve performance, more pre-trained CNN models can be used.

Hamayun et al. [55] considered "Classifier Ensemble" techniques and "Feature Fusion" to propose an adaptable face recognition system. To achieve enhanced classification results, they used a "Classifier Ensemble" technique, rather than a single classifier. The type and number of base classifiers, type of features, dimensionality of features collected in the feature space, and ensemble learning techniques, are the various factors that influence the performance of their classification system.

D. LITERATURE REVIEW RELATED TO FACE RECOGNITION IN FORENSICS

Chijindu and Chinagolum [1] presented a novel system that differentiates two similar suspected faces of different identities using a bag of features by applying machine learning algorithms to recognize identical twins to support global crime investigation. This study has successfully provided a new pathway to support digital forensic investigation by, employing artificial intelligence (machine learning) to improve the existing face recognition systems. The accuracy and time taken in the recognition process of this system can be further improved using a "K-NN" classifier or a "Neural Network" instead of a "Support Vector Machine".

Forensic Image Analysis [56] is a new set of parameters that uses indices to derive image ratio-based facial features defined geometrically. This rule book probes one to investigate the possibility of deriving multiple anthropometric measurements and their ratios to enhance face recognition accuracy.

Tauseef Ali et al. [57] reviewed forensic facial identification, a forensic expert method for manual facial comparison. The Bayesian framework is discussed and how it can be adapted to forensic face recognition is elaborated. Several issues related to court admissibility and reliability of the system are also discussed.

Rodriguez et al. [58] projected the use of a Bayesian probabilistic framework to discuss a method of presenting evidence evaluation in court. Institutions such as ENFSI encourage the use of a Bayesian framework to report evidence to the Court of Justice as a suitable way to standardize reasoning. Three different open-source automated systems such as "OpenFace", "SeetaFace", and "FaceNet" - all three based on "Convolutional Neural Networks" were used in this approach, after which the similarity or distance obtained is then converted to a likelihood ratio. The obtained LR was validated in a courtroom by a human expert.

Ounachad [59] used "Golden ratio" based- features and "Bayes Classifier" to present an approach for the classification of gender and recognition of humans based on their face sketch images. The approach includes computing two golden ratios namely width face ratios and height face ratios. To develop a criminal identification process, classification, and recognition are performed using golden ratios and Bayes classifiers.

III. RESEARCH METHODS

A. METHODOLOGY

A framework for the recognition of different face categories such as the same images, different images, and look-alikes using facial images is presented to make a perfect decision in face identification using machine learning algorithms.

- **Overview of the proposed approach**
  Two-dimensional (2D) facial images were selected from the dataset. Every chosen image underwent pre-processing for the detection and normalization of the face. The proposed system was used to accurately localize 468 landmarks on 2D facial images, and these landmarks were overlaid on a 3D facial image using which a 3D face mesh was generated. Feature extraction is then performed by measuring distances between pairs of anthropometric points using "Euclidean Distance", and "Geodesic Distance". Their ratios are based on curves, and the curvature characteristics are used to generate a fusion of features. The results are given as inputs to multiple classifiers such as XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers. To select the top-performing machine learning models, the lazy-Predict package was used, which compares the effectiveness of various machine learning models for a dataset. The performance of this framework was evaluated for accuracy, error rate, recall, precision, and F-measure.

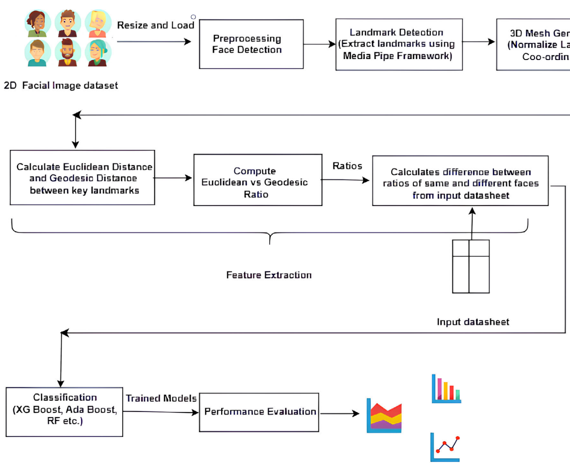

FIGURE 5. Schematic illustration of the proposed methodology.

Pre-processing, face detection, landmark detection, 3D mesh generation, feature extraction utilizing Euclidean and geodesic distances, classification, and performance evaluation are the various phases of face comparison and authentication, as shown in Figure 5.

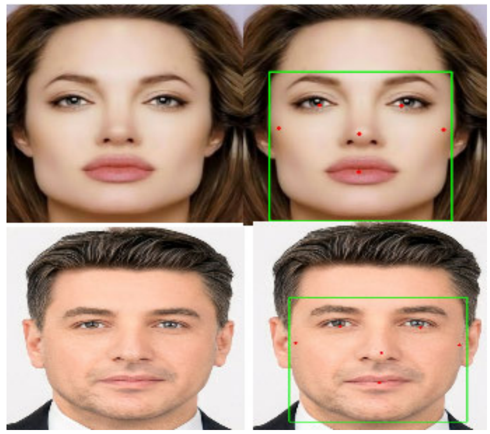

FIGURE 6. Face detection before and after with 6 landmarks using Mediapipe framework.

1) **Pre-processing:** 2D face data were acquired to provide "clean" faces for detection and normalization. In the proposed approach, a face image is initially selected, and pre-processing operations such as cropping and scaling are performed to generate a facial image dataset.
2) **Face Detection:** This is the process of detecting a human face in an image using a set of data. Detecting the face in photographs is difficult because the identified findings are based on several elements, such as the environment, illumination, movement, orientation, and facial emotions. Using MediaPipe, drawing face landmarks and face detection are simple processes [30]. In the proposed method, face detection is performed using Mediapipes' face detection model, which detects the face in real-time using an image or video as the input. Figure 6 displays the outcome of the face image before and after face detection.
3) **Landmark Detection:** This enables the accurate and reliable identification of facial landmarks. A few precise images were mapped onto individual facial photographs to obtain the required measurements. The proposed approach was used to locate and extract features automatically. In the present work, 468 landmarks were extracted instead of 68 to improve the accuracy using the Mediapipe library [36], [37], [38], [39], [40], [41]. The media pipe framework was used to detect multiple faces and 468 face landmarks in a 3D space. This face geometry solution estimates 468 face landmarks in real-time, even on mobile devices.
4) **3D Face Mesh Generation:** A total of 468 landmarks extracted from the 2D facial image were overlaid on the 3D image to generate a face mesh, which is a 3D model of the face. The face mesh detection API creates a face mesh with 468 3D points, edges, and triangle information for each detected face.
   In Figure 7, the results of face landmark detection using number notation and mesh generation are displayed.

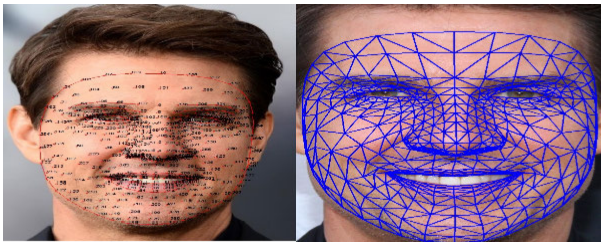

FIGURE 7. Overlaying of 468 landmarks using number notation and face mesh on the facial image.

5) **Feature Extraction:** This process obtains digital details, figures, or particulars from raw data from the most distinctive region extracted. Only discriminatory information was contained in the retrieved features, which were used to identify individuals. The present study used both Euclidean and geodesic distances and their ratios as features. Feature extraction is proposed for the entire face by calculating the Euclidean and geodesic distances between facial geometric points based on the Anthropometric Model. The geodesic distance is based on curve and curvature characteristics, and the Euclidean distances between facial fiducial points and their ratios were computed. Table 2 illustrates the sample Linear and Geodesic Distances used in the proposed approach for facial analysis in four facial regions: the forehead/eyes, nose, lips, and chin. This is broadly used to illustrate faces that are measured from 468 landmarks, namely "Anthropometric Reference Points."
6) **Classification:** This is the process of arranging data into labeled classes using a classifier algorithm. The classification results were based on two image classes: SAME and DIFFERENT. In the proposed approach, the extracted ratio-based features are given as inputs to multiple classifiers such as XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers. These classifiers are used to learn discriminatory features to develop a perfect system for face recognition and verification of criminals that support and improve forensic investigation.
7) **Performance Evaluation:** Performance results of the proposed framework are evaluated for Accuracy, Error rate, Recall, Precision, and F-measure.

1) DATA COLLECTION AND DESCRIPTION

A data set comprising 600 images of faces collected from different sources (public) which include individual male and female faces, different images of the same person, look-alikes, and other issues are used in the proposed study as shown in Figure 8.

The format used for representing images in the dataset follows JPEG and PNG. From the dataset, 70% of the images were used for training, and 30% of the images were used for testing. The preliminary step after obtaining the dataset is eliminating noise using suitable pre-processing techniques (removing noise from the images eg. Gaussian Blur, resetting the image resolution to extract necessary features, Morphological Transforms may be used to enhance the foreground and background of the image, aligning and rotation of images, suitable scaling).

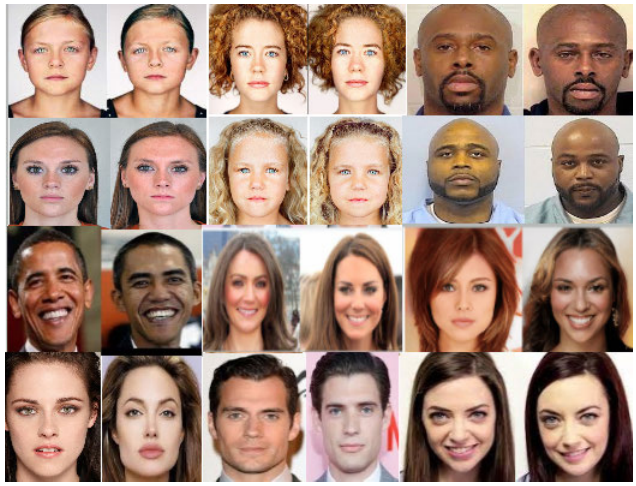

FIGURE 8. Sample facial images of the dataset created.

2) FACIAL IMAGE ANALYSIS

Face analysis is the practice of analyzing human faces in real-time, as well as in videos or images, using computer algorithms and machine learning techniques. For humans and computer systems, a face image conveys details like age, identification, gender, race, mood, and attractiveness. Machine learning-based face analysis techniques have drawn much attention in recent years due to the wide range of tasks they may be used to. There has been an ongoing passion in this area regarding finding faces, locating facial features, interpreting facial photos, and identifying faces. Facial analysis involves locating and quantifying facial features in an image.

In the proposed study, a human face image was selected on which the anthropometric landmarks were plotted (Table 1). Subsequently, the facial image is analyzed for feature extraction by measuring the distances between any two landmarks using Euclidean and geodesic distances along the face curve. Sample landmarks are shown in Figures 9 and 10 because manual annotation of 468 points is difficult.

In addition, 32 distances between landmarks were proposed, including Ft-Ft, Tr-G, Enl-Enr, Exr-Enr, Exl-Enl, Sn-N, Prn-Sn, N-Prn, Ls-Gn, Ls-Li, Zy-Zy, Chl-Chr, Exl-Chl, Exr-Chr, Exl-Prn, All-Chl, Alr-Chr, Alr-Prn, Alr-Sn, Ps-Pi, Ls-N, Sto-Sn, and Gn-N. Figures 9 and 10, show the analysis of facial images using the anthropometric landmarks of various facial regions. Facial image analysis performed in 3D space is represented here by considering 2D facial images.

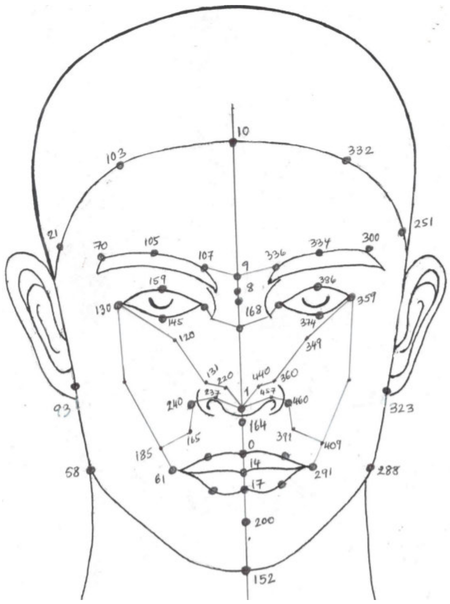

FIGURE 9. The facial image analysis using sample anthropometric landmarks.

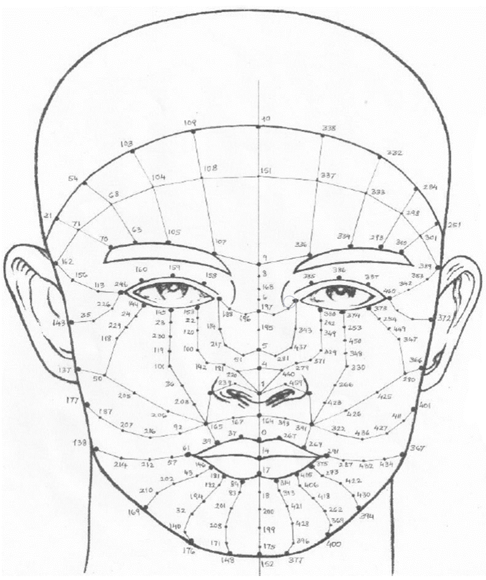

FIGURE 10. The facial image analysis using most significant anthropometric landmarks.

3) COMPARISON OF ESTABLISHED METHODS

Face marking is the process of detecting and localizing certain characteristic points on the face. It has proven extremely challenging owing to confounding factors such as significant facial appearance changes under different facial expressions and head poses, facial occlusions by other objects, and environmental conditions such as illumination. There are many applications in real-world capturing conditions, but they lack quality. The following well-known facial landmark detection methods have better accuracy but fail in certain applications. However, the number of facial landmarks is insufficient to obtain sufficient information from facial images.

- **A multi-task cascaded convolutional network (MTCNN) [42], [43]:** is a neural network that uses relatively light CNNs to detect facial regions and extract an alternative 5-point facial landmark detector, namely the left eye, right eye, nose, and two corners of the mouth in real-time. It is built in the form of a three-network cascade: a Proposal Network (P-Net), an Output Network (O-Net), and Refine Network (R-Net). Although the face detection score was high for the MTCNN model, the speed was low. The advantage of MTCNN is that it can identify occluded faces with some accuracy. However, the MTCNN with five landmark points was not sufficient to improve the face recognition accuracy.
- **The digital library (DLIB) [35], [44], [45]**: is the most popular open-source machine learning library called Dlib's 68-point facial landmark detector which includes the chin and jawline, eyebrows, nose, eyes, and lips in 2D space. The pre-trained facial landmark detector inside the dlib library was used to estimate the location of 68 (x, y)-coordinates that mapped to the facial structures on the face. Although the algorithm is still actively used in modern research, unfortunately, the number of points used in the above model is not sufficient to describe all regions of the face especially the forehead region, which is mostly ignored. However, in the proposed study, landmarks of the forehead region were required. Although Dlib is highly accurate for extracting points from frontal faces, this model does not hold effectively about high pose variation.
- **Mediapipe Framework [36], [37], [38], [39], [40], [41]**: is an open-source, cross-platform, face geometry solution library developed by Google for computer vision tasks. It estimated 468, 3D face landmarks in real-time, even on mobile devices. The Mediapipe Python library uses a holistic model to detect multiple faces and 468 face landmarks in a 3D space. The Mediapipe framework provides more information than needed, and it is also possible to select only essential information with real-time performance. Applications currently implemented with Mediapipe include face detection, face mesh annotation, iris localization, hand detection, pose estimation, hair segmentation, object detection, tracking, and three-dimensional(3D) object detection. Based on the literature, it is inferred that DLIB is relatively slower in terms of face and landmark detection capability compared to the Mediapipe framework when considering applications such as active face detection in live video or any other similar applications.

In the current study, the face mesh solution from the Mediapipe framework was employed to annotate the 468 landmarks in any uncontrolled condition (including the entire forehead region and extra points on the jawline region) from which significant landmarks were selected to obtain an increased number of variances that enhanced the recognition accuracy. Forensic experts in criminal investigations rely only on anthropometry-based landmark measurements

TABLE 2. Linear and geodesic distances used in the proposed research work.

Landmarks	Facial Distance	Distance Type
Ft-Ft	Forehead width	Geodesic
Ex-Ex	Outer canthal width	Geodesic
Ex-Ch	Upper cheek height	Geodesic
Tr-G	Forehead height	Geodesic
Sbal-Sbal	Alar base width	Linear
N-Prn	Nasal bridge length	Geodesic
N-Sn	Nose height	Geodesic
Sn-Prn	Nasal tip protrusion	Geodesic
Sn-Sto	Upper lip height	Geodesic
Sn-Sto	Upper lip height	Linear
Ls-Li	Lip height	Geodesic
Ls-Li	Lip height	Linear
Chi-Chi	Mouth breadth	Geodesic
Sn-Gn	Lower facial height	Geodesic
Enl-Enr	Intercanthal width	Geodesic
Zy-Zy	Bizygomatic breadth	Geodesic
Zy-Zy	Bizygomatic breadth	Linear
Go-Go	Bigonial breadth	Geodesic

that are widely accepted in the court of law as statistical evidence therefore using a deep-leaning-based approach is not acceptable. Hence, the Mediapipe framework which works well even in real-time images, is used in this approach for landmark detection.

4) FEATURE EXTRACTION

The left/right eyebrow width, left/right eye width, left/right eye height, nose width, height, lip height, chin height, mouth-to-nose ratio, mouth height, and breadth were measured. Table 2 provides the definitions of the Linear and Geodesic Distances used in the proposed approach. The Euclidean and geodesic distances were measured from 468 already located facial landmarks, and their related ratios were calculated.

1) **Extracting the features using Euclidean distance** The Euclidean distance between points P-Q is the length of the line segment connecting PQ as shown in Equation(1).

$$d(P, Q) = \sqrt{(p1 - q1)^2 + (p2 - q2)^2} \quad (1)$$

where

- where (p1, q1) are the coordinates of a single point.
- (p2, q2) are the coordinates of other points.
- d is the distance between (p1, q1) and (p2, q2)

In three-dimensional Euclidean space, the distance is given by equation (2).

$$d\,(p, q) = \sqrt{\sum_{i=1}^{3} (p_i - q_i)^2} \quad (2)$$

Figure 11 shows the feature extraction process using the Euclidean distance from an individual face in 2D.

2) **Extracting the features using geodesic distance** A geodesic is a curve that represents the shortest path (along the curve) between two points on the surface.

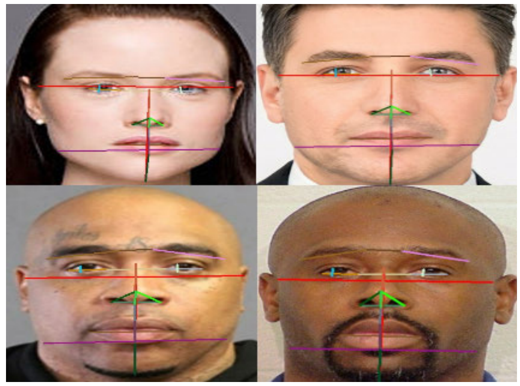

FIGURE 11. Feature extraction using Euclidean distances in 2D facial images [60], [61], [62].

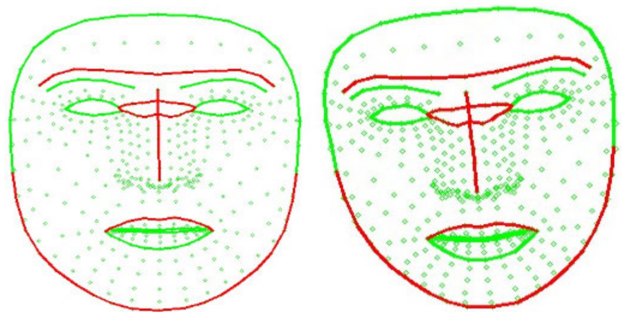

FIGURE 12. Geodesic distance based Feature extraction from bizygomatic breadth (zy-zy); Nose height(n-sn); Upper lip curve(ChL-ChR); Lower and upper nose bridge (EnL-EnR) etc.

In 3D geometry, a point has x, y, and z coordinates. The shortest distance between points A (x1, y1, z1) and B (x2, y2, z2) in three dimensions is the square root of the sum of the squares of the difference between the corresponding coordinates as expressed in Equation (3).

$$d(P, Q) = \sum_{i=1}^{n} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2 + (z_{i+1} - z_i)^2} \quad (3)$$

where n denotes the number of landmarks.

Figure 12 shows the extraction of facial features from different facial regions of individual faces with pose variations using geodesic distances.

5) IMPLEMENTATION DETAILS

The Mediapipe Framework, OpenCV, and Tensor Flow were used for face, landmark detection, and mesh generation. Algorithms 1, 2, and 3 explain the feature extraction process of the proposed approach.

Algorithm 1 Extraction of Facial Features

Input: Facial images
Output: Feature difference between two images

```
procedure Feature extraction
    if Geodesic distances are not calculated then
        for each image in the dataset do
            calculates the geodesic distance of given landmark points
            store it in the temp buffer
        end for
        Write temp buffer to Index file
    end if
    for each row in extractor do
        get the geodesic distance of target_image from the index file
        store it in A
        get the geodesic distance of test_image from the index file
        store it in B
        get a classification from the Classification column
        store it in C
        calculates the difference between A and B
        store it in the temp buffer
    end for
    Write temp buffer to differences file
end procedure
```

Algorithm 2 Finding the Differences Between Target and Test Images Using Geodesic Distances

Input: Dictionary containing the various regions for which geodesic distances have to be calculated and the image on which the calculation has to be performed.
Output: Array containing Geodesic Distances for regions in Points_Dictionary.

```
procedure Calculate Geodesic Distances (Points_Dictionary, Face_img)
    calculate Landmarks of Face image and store in landmarks
    for each list(points) in Points_Dictionary do
        find the points in landmarks and store them in tmp1
        call Geodesic(tmp1) and store the result in the temp buffer
    end for
    returns the temp buffer
end procedure
```

Algorithm 3 Geodesic Distance Computation

Input: Array of points
Output: Geodesic distance

```
procedure Geodesic distance computation
    for each point A in input do
        distance += distance_of_points (A, A + 1)
    end for
end procedure
```

6) CLASSIFICATION USING MACHINE LEARNING ALGORITHMS

A classifier segregates data into labeled classes. Using the Lazy-Predict package, 27 classification models were created, and the top ten models such as XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers that performed the best (with the highest accuracy in the least amount of time) were chosen in this study to develop a perfect system of face recognition and verification that supports and improves forensic investigation. Using a dataset, the Lazy Predict Python package was used to compare the effectiveness of the various machine-learning models. Supervised learning models have several forms. Models such as XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers, were used in this study for better accuracy and to develop a perfect system of face recognition and verification that supports and improves forensic investigation. To test the model's performance, precision, accuracy, sensitivity, specificity, FNR, F-measure, and FPR were also measured. To find the best solution, you need to conduct many experiments, evaluate machine learning algorithms, and tune their hyperparameters. The default values for their hyperparameters are provided in most machine learning algorithms. However, the default values only sometimes work effectively on various machine learning tasks. Because of this, you must optimize them to find the ideal combination that will deliver better and more effective outcomes on the data in a reasonable time. Classifiers in this research, such as XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers, all have a few hyper-parameters which need to be significantly modified. Therefore, one can determine the best parameters by using various hyper-parameter optimization methods such as Grid Search, Random Search, etc.

7) HYPER-PARAMETER OPTIMIZATION

Tuning the hyper-parameters of machine learning algorithms is a time-consuming task, yet an essential operation. The selection of hyper-parameters can significantly affect the performance of the algorithm. Determining the appropriate hyper-parameter values for a specific machine learning algorithm and a specific dataset is known as hyper-parameter tuning or hyper-parameter optimization. Hyperparameter optimization is selecting the ideal set of hyperparameter values during model training. Hyperparameters are used to regulate the learning process and have a substantial impact on the effectiveness of machine learning models.

To improve the performance of the proposed models, hyper-parameter tuning methods are used. Since Grid Search and Random Search [64], [65] are the simplest, basic, and most common methods. Using the Grid Search method, one can construct a model for every possible combination of the supplied hyperparameter values, evaluate each model, and choose the best design. To identify the optimal solution for the created model, the random search technique uses random combinations of the hyperparameter values. In the proposed study these two methods are considered to begin with to find the best hyperparameters for each algorithm as listed in Table 3 which results in better accuracy for the mentioned machine learning models therein. For e.g. parameters of the XGBoost classifier with the learning_rate = 0.01. The parameter n_estimators for the Adaboost classifier are 100. For SVM, a polynomial kernel function is chosen with an optional constant C = 0.01. Using both hyperparameter tuning methods, the performance of each machine learning model is analyzed. Preferences depend on the nature of machine learning models and the dataset used. As per our research work, there are other optimization techniques like Bayesian, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), etc. that could be considered in further studies.

The learning rate is a hyperparameter that determines how much to alter the model each time the model weights are updated in response to the predicted error. The ''learning rate'' or ''step size'' refers to how frequently the weights are updated during training. If the learning rate is very high, the ideal solution will be skipped. We will require too many iterations to reach the best values if it is too tiny. The learning rate is a hyperparameter that has a tiny positive value, frequently in the range between 0.0 and 1.0. This influences the performance of machine learning models. In the proposed study, for e.g., when the learning rate was 0.01, the best performance was 78 for XGBoost and when the learning rate was 0.1, the best performance was 77% for AdaBoost and 68% for NB. This work observed that the models were able to achieve the highest accuracy with a low learning rate. Since we have obtained the best accuracy considering a small dataset using hyperparameter optimization, the performance of the listed machine learning models has not been tested using different learning rates. Choosing an appropriate learning rate is still a problem leading to low accuracies in classification.

The accuracy of the machine learning techniques, namely XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers, was optimized. Hyperparameter modification has been shown to improve the classifier performance, especially regarding accuracy. Compared to the other models, AdaBoost and RF exhibited the strongest performance in terms of classification accuracy. From the experiments, it was determined that XGBoost is the best classifier. The best hyper-parameters selected through optimization for various machine learning algorithms are listed in Table 3.

8) IMPACT OF THE PROPOSED SYSTEM ON FORENSIC CASE ANALYSIS

Forensic science involves implementing scientific standards to examine facts and evidence collected by the law enforcement department to identify suspects with immense convictions under the legal system. Face capture, which is unobtrusive and natural, has emerged as one of the best biometrics for facial recognition. The accuracy of identifying individuals has gained considerable attention in recent years. Facial recognition algorithms should work consistently for look-alike faces and identical twins. Nonetheless, face recognition systems today face a tremendous challenge in identifying identical twins owing to the similarity of their genes, making them unable to distinguish from one another by standard forensic DNA testing. Identical twin birth rates seem to have increased, contributing to fraud and crime rates. If one of the identical twins/look-alikes commits a grave crime, their uncertain personality leads to uncertain decisions during court trials. According to recent studies, identical twins do not perform well when facial recognition systems are used compared to others. Mistaken identification must not

TABLE 3. Machine learning algorithms and best hyper-parameters selected through optimization.

Algorithms	Hyper-parameters
The XGBoost (eXtreme Gradient Boosting)	{ learning_rate =0.01, min_child_weight=1, objective= binary:logistic, nthread=4, scale_pos_weight=1, seed=42, n_estimators=5000,,n_jobs=1, cv=5 }
AdaBoost Classifier	{ learning_rate: 0.1, n_estimators: 100 }
Random Forest classifier	{ Classifier: RandomForest, n_estimators: 390, max_depth: 33.43073482586823 }
Logistic Regression	{ C: 0.008301451461243866, penalty: none, solver: newtoncg }
Extra Trees Classifier	{ class_weight=balanced,n_jobs=-1, random_state=42 }
Bernoulli Naive Bayes Classifier	{ alpha:0.1, binarize: None, class_prior: None, fit_prior: False }
LightGBM Classifier	objective: binary, metric: binary_logloss verbosity:-1, boosting_type:gbdt feature_pre_filter: False, lambda_l1:9.374401530383671e-08, lambda_l2:3.7998370148638856e-08, num_leaves: 31, feature_fraction: 0.5, bagging_fraction:0.4131678706278327, bagging_freq: 5, min_child_samples: 5, num_iterations: 1000 }
Nearest Centroid Classifier	{metric: euclidean, shrink_threshold: 0.05 }
Support Vector (SVC) Classifier	{ C:0.01, degree: 3, gamma=0.1, kernel: poly }
Decision tree	{ max_depth: 30, max_features: 5, min_samples_leaf: 5, min_samples_split: 15 }

occur when employing a bio-metric identification approach to prevent unintentionally convicting innocent persons. The case histories of such crimes are mentioned in [1]. For the DNA test, identical twins were suspected in the rape of six women. However, we were unable to ascertain the one who assaulted, [2] a murder case in which one of the twin brothers was the suspect responsible. The issue came to premature closure since the Biometric Verification was not good enough to implicate the suspect; in another incident, instead of apprehending a warlord leader at gunpoint, the murder of an innocent individual took place because of the similarity in the facial features. In addition, criminal suspects with look-alike faces pose a significant challenge to forensics-related illegal and fraudulent activities.

In the time of technological advancement for solving criminal cases, increased crime rates persisted. The Judiciary system performs best in punishing actual culprits without delay. However, the judiciary system cannot provide justice for cases with identical twins and faces. Society in general and the innocent need assurance in getting justice from the judiciary system to accurately recognize criminals with similar faces or identical twins, thereby not wrongly punishing the innocent. It not only takes up clinical forensic medicine work in the form of examination of victims and accused of sexual assault, age estimation, issuing wound certificates, and examination of drunkenness cases, but also performs DNA, fingerprinting, and facial analysis of the criminal. A new set of parameters using indices/indices to derive image ratio-based facial features was geometrically defined for forensic Image Analysis [56]. This rule book probes one to investigate the possibility of deriving multiple anthropometric measurements and their ratios to enhance face recognition accuracy. Currently, biometric image analysis is performed manually using anthropometric and morphometric measurements to generate evidence based on experts' opinions which can be presented in a court of law. There is an impending need to blend their manual approach with the AI/ML approach to provide effective evidence with better accuracy in real-world forensics [57]. Additionally, integration with the court's legal system should provide adequate evidence with better accuracy in real-world forensic studies. Improving the existing FRS with the help of the proposed system can help expedite the identification of culprits, especially when considering similar faces and identical twins with effective accuracy to reduce fraud and crime rates. The environmental impact of FRS can range from minor to significant owing to its broad applicability in various fields.

The FRS is intended to benefit from infinite ways: law enforcement from various perspectives, human trafficking, healthcare, and commerce. The impact can be assessed by considering the different elements of the FRS, incrementally, comparatively, and meticulously clarifying the primary purpose and usage, various risks and assistance required, and subjective judgment with necessary validation.

IV. RESULTS AND DISCUSSION

This section describes the system's result. 70% of the data in this study come from training, whereas 30% come from testing. To achieve the best level of accuracy, a variety of machine learning techniques, hyper-parameters, and performance measures are employed.

To identify criminals in facial images, the performance of several supervised ML classifiers was measured using test data based on a confusion matrix using different classification algorithms for the dataset. Different evaluation metrics were used to justify the comparative analysis. The number of accurate and incorrect predictions is calculated using a confusion matrix, which is supplied by the sklearn metrics module and is used to obtain precision, recall, accuracy, and other metrics.

TABLE 4. Confusion matrix.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	*TP*	*FP*
	Negative (0)	*FN*	*TN*

Table 4 presents the confusion matrix with true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). For TP predictions in a binary classification issue, the model accurately predicts the positive class (both the prediction and the actual are positive). The model successfully predicts the negative class for TN (both predicted and actual are negative). In the case of FP predictions (TYPE I error), the model provides an incorrect prediction for the negative class (predicted-positive, actual-negative). The model mispredicts the positive class for FN Predictions (TYPE II error) (predicted, negative, and actual-positive). Based on the confusion matrix, the following measures are commonly used to analyze the performance of classifiers based on supervised machine learning algorithms.

1) **The accuracy** is the prediction of the model provided by the sklearn-metrics module. It is an indicator of the model's overall effectiveness and a measure of how well it can classify data. A confusion matrix was used to calculate the accuracy. This is calculated using Equation (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

where TP and TN are correct predictions. FP and FN represent incorrect predictions.

2) **Precision** is the proportion of correct positive predictions. It is calculated using Equation (5).

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

3) **Sensitivity/Recall** was calculated as the number of correct positive predictions divided by the sum of the true and false positives which is also called the true positive rate (TPR). The best sensitivity was 1.0, and the worst was 0.0. It is calculated using Equation (6).

$$Sensitivity = Recall = \frac{TP}{TP + FN} \tag{6}$$

4) **Specificity** was calculated as the number of correct positive predictions divided by the sum of TP and FN values. This is called the true negative rate (TNR). It is calculated using Equation (7).

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

5) **The F1-score** is the harmonic mean of precision and recall such that the most significant score is 1.0 and the bad score is 0.0. It emphasizes both false positives and false negatives. It is calculated using Equation (8).

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{8}$$

The number of correct and incorrect guesses was calculated in the Confusion Matrix, which is then summarized with the number of count values and broken down into each class. The Confusion matrices for the XGBoost, AdaBoost, RF, and LR models are shown in Figure 13.

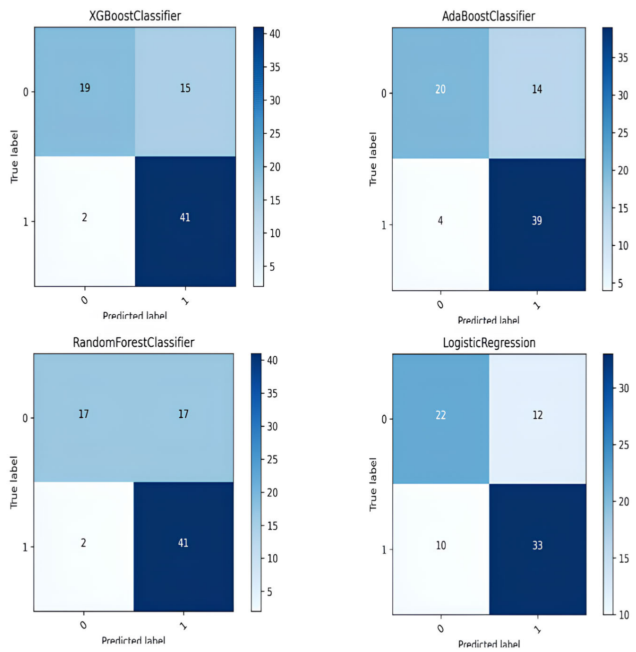

FIGURE 13. Confusion matrix for the XGBoost, AdaBoost, Random Forest, and logistic regression classifiers.

Table 5 shows the classification accuracy of the various machine-learning algorithms obtained for the same or different facial images.

Performance evaluation was performed based on sensitivity, specificity, and classification accuracy. The precision, recall, F1-score, and accuracy of the model are summarized in the classification report. Table 6 represents the performance of the XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers in terms of machine learning techniques.

By plotting the FPR along the X-axis and the TPR along the Y-axis at various threshold settings, a Receiver Operating Characteristic (ROC) curve was formed which is the sensitivity as a function of the FPR. The models were better at

TABLE 5. Classification accuracy of various machine learning algorithms.

XGBoost	AdaBoost	RF	BNB	DT	LR	LGBM	XtraTree	SVM	NC
78%	77%	75%	68%	57%	71%	58%	57 %	58%	62%

TABLE 6. Classification report of various machine learning models.

No	Methods	Class	Precision	Recall	F-Measure
1	Extreme gradient boosting (XGBoost)	Same	0.90	0.56	0.69
		Different	0.73	0.95	0.83
2	Adaptive Boosting (AdaBoost)	Same	0.83	0.59	0.69
		Different	0.74	0.91	0.81
3	Random Forest (RF)	Same	0.89	0.50	0.64
		Different	0.71	0.95	0.81
4	Bernoulli Naive Bayes (BNB)	Same	0.71	0.44	0.55
		Different	0.66	0.86	0.75
5	Decision Tree (DT)	Same	0.52	0.41	0.46
		Different	0.60	0.70	0.65
6	Logistic Regression (LR)	Same	0.69	0.65	0.67
		Different	0.73	0.77	0.75
7	Light Gradient Boosting Model (LGBM)	Same	0.55	0.35	0.43
		Different	0.60	0.77	0.67
8	Extra Tree Classifier (ETC)	Same	0.53	0.24	0.33
		Different	0.58	0.84	0.69
9	Support Vector Machine (SVM)	Same	0.53	0.50	0.52
		Different	0.62	0.65	0.64
10	Nearest Centroid (NC)	Same	0.60	0.44	0.51
		Different	0.63	0.77	0.69

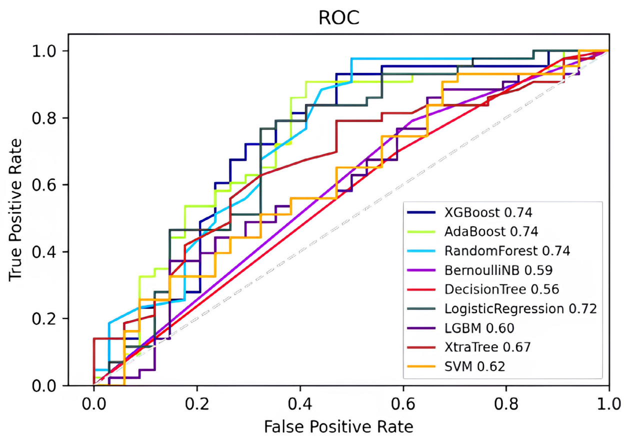

FIGURE 14. Receiver operating characteristic of various machine learning models.

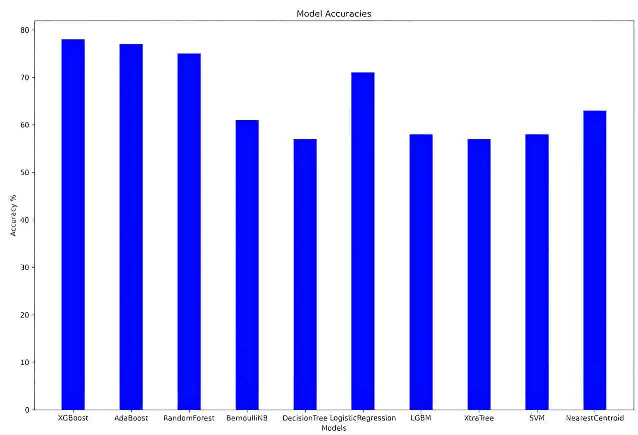

FIGURE 15. Accuracy comparison bar chart of various classifiers.

identifying the positive and negative classes in the data as they approached the top-left corner. A model that randomly predicts the class is denoted by a ROC curve near the diagonal line. Figure 14 shows the ROC Curve of machine learning classifiers such as XGBoost, AdaBoost, RF, NB, DT, LR, LGBM, ETC, SVM, and NC classifiers, where random guessing with AUC=0.5 is specified by a dotted line.

The Area Under the Curve (AUC) was applied in the classification to determine which model predicted the best results. According to the ROC curves, XGBoost, AdaBoost, and RF outperformed the other models in terms of the AUC. In this Figure, the area under the curve (AUC) of XGBoost, AdaBoost is 0.74%, Random Forest is 0.74%, Logistic Regression is 0.72%, Extra Tree Classifier is 0.67%, Light Gradient Boosting Model is 0.60%, and SVM is 0.62%, respectively.

Figure 15 shows the accuracy comparison bar chart of the various classifiers for the different categories of facial images. The evaluation and validation of the performance and quality analysis of the facial images were based on the accuracy, specificity, and sensitivity of the experimental results of the proposed technique.

The experimental results show that XGBoost is the best classification model that provides the best accuracy (78%) for predicting facial images compared with AdaBoost (77%), RF (75%), NB (68%), DT (57%), LR (71%), LGBM (58%), ETC (57%), SVM (58%), and NC (62%) classifiers which can be further increased by considering a greater number of images in the dataset. Experiments showed that XGBoost was the best classifier. AdaBoost performed the best, whereas RF and LR performed better than the other algorithms in terms of sensitivity, specificity, and error rate. The final results of the model classification were compared to determine which approach had the best accuracy and enhanced the performance of the model. In this experiment, tree-based machine learning algorithms such as XGBoost outperformed statistical models like SVM and BNB primarily because they did not need pre-processing features like standardization or normalization.

The tree-based models needed bagging and boosting to improve the model's accuracy, which was the other justification. The decision tree underperformed the random forest in this experiment. When compared to predictions made with a single model, such as a Decision Tree, ensemble techniques, like Random Forest, are often more accurate. Due to the use of a leaf-wise split technique rather than a level-wise split strategy, LGBM beat decision trees in terms of complexity. Although Random Forest and Extra-Trees were surprisingly comparable ensemble algorithms, Extra-Trees performs worse than Random Forest. The difference was that whereas the extra trees approach used the complete original sample, the random forest algorithm only used subsamples of the input data with replacement. Even when trained on the same data set each time, the machine learning models produce different predictions each time, and when evaluated, they may have a varying level of error or accuracy.

The machine learning models make different predictions each time it is trained, even when it is trained on the same data set each time, and when evaluated, may have a different level of error or accuracy. This is expected to be the feature of the algorithm and Variations due to the type and characteristics of the data (data set size, quality, variance, overfitting, and underfitting), the learning algorithm (deterministic, stochastic), the evaluation procedure (train-test split ratio and k-fold cross-validation), ensemble learning algorithms, the selection of optimal parameters, bagging, boosting, etc. As a result, it can be difficult to choose a learning algorithm that is appropriate for the intended use in a particular domain. The reason for this is that various learning algorithms serve a variety of purposes, and even results from algorithms belonging to the same general category can differ depending on the characteristics of the input data. Therefore, it's crucial to understand the fundamentals of different machine learning algorithms and how they might be used in diverse fields of real-world application.

V. CONCLUSION AND FUTURE WORK

The problem of facial similarities, such as look-alikes and identical twins, especially in criminal situations, presents a significant barrier in forensic investigation and detection. The proposed method in this work recognizes faces by employing 2D facial images collected from the web to approximate a 3D face mesh using 468 landmarks of media pipe framework, measuring euclidean and geodesic distances and their ratios, as well as utilizing different classifiers that can provide the correct matching decision in an unrestricted environment. The use of hyperparameter optimization for comparing the recognition performance of machine learning models statistically resulted in showing that the Extreme gradient boosting classifier gives the best accuracy (78%) for predicting facial images compared with Adaptive Boosting (77%), Random Forest (75%), Bernoulli Naive Bayes (68%), Decision Tree (57%), Logistic Regression (71%), Light Gradient Boosting Model (58%), Extra Tree Classifier (57%), Support Vector Machine (58%), and Nearest Centroid (62%) classifiers.

Being able to distinguish between similar faces such as look-alikes and identical twins is still a difficult challenge, thus our future study will involve building a multi-modal FRS system utilizing a variety of modalities to address the challenge. Future work will also look into more reliable methods to increase the accuracy of the current study by developing a larger dataset of face images and the best classifier.

CONFLICTS OF INTEREST

The authors have no conflicts of interest to declare.

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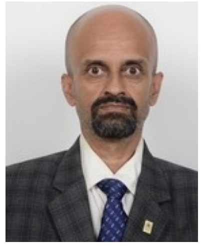

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