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AI-BASED HUMAN FACIAL RECOGNITION USING DEEP LEARNING WITH YALE FACE DATASET

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ABSTRACT

Human Faces as a biometric feature are applied in multiple applications where both public and private organizations have preserved facial images for membership cards, passports, or personal identifications. They have been used as referential databases in investigations and match facial images of victims, witnesses, or offenders. Moreover, the widespread usages of smartphones and digital cameras have made it simple to share created facial images using social networks. Thus, Human Facial Recognitions (HFRs) have been an exciting and quickly expanding field of study. Real time applications include HFRs for identifications, access controls, forensics, and human-computer interactions. Though studies have been proposed for HFRs, there are areas that are wanting in implementations. Hence, this work attempts to fill up these gaps in HFRs with its suggested AI Based Recognitions of Faces (AIBRF). The schema uses Deep Learning (DL) techniques for identifying faces. The schema is trained using Yale Face dataset and achieves 99% accuracy in HRFs.

KEYWORDS

HFRs; face analysis, face database, Deep Learning, yale faces, facial detections.

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1. INTRODUCTION

Technological HFRs have expanded rapidly, becoming an essential component of security systems, personal devices, and even shopping experiences. HFRs have found use in surveillance, security, and authentication applications. It is widely utilized in applications such as smartphone unlocking, social media image recognition, and even public-area security monitoring. HFRs use facial features to identify or validate based on their distinctive features. Subsequently, this data is transformed into a digital representation, which is frequently referred to as a facial template. The technique compares a person's face to a database of recognized faces after taking a image or video of their face. If a match is discovered, the system can either verify that the individual is who they say they are or validate their identification. Depending on the application, this process may be carried out in batches or in real time. Over the past three decades, HFRs have drawn a lot of attention in research because they are thought to be a simplified form of image analysis and pattern recognition. By examining face traits, HFRs driven by artificial intelligence (AI) are used to identify people. Applications of AI HFRs include: Identity Verifications (used in passport authentication, smartphone unlocking, and online identity verification processes); Healthcare (helps diagnose genetic disorders with distinctive facial characteristics and verify patient identities); Retail and Marketing (used for personalized experiences and customer analytics); and Security and Access Controls (used in airports, commercial buildings, and residential facilities for secure entry). Human faces are biometric traits that assist realistic authentications or identifications (Sinha, Balas, Ostrovsky and Russell, 2006). However, proper confirmation of fingerprint or iris identification necessitates the expertise of a specialist. HFRs, unlike fingerprint or iris scans, are non-invasive and may be generated quickly without physical contacts (Ouamane, Benakcha, Belahcene and Taleb-Ahmed, 2015). A British court documented the earliest attempt to identify a face by matching segments of facial image graphs in 1871 (Porter and Doran, 2000). HFRs are also among the most important law enforcement tools in situations when there is available video or image graphic evidence of a crime scene. Computer scientists, psychologists, and neurologists have long been intrigued by HFRs (O'Toole, Roark and Abdi, 2002), though human faces are not the best of modalities and they can be altered by lighting, disguises, and makeups (Dantcheva, Chen and Ross, 2012). Fig. 1 depicts important historical periods characterized by advanced HFR.

Bledsoe et al. (1964), American researchers, investigated HFR computer programming. They foresaw a semi-automated process in which consumers enter twenty computer measurements, such as eye or mouth size. In 1977, the system was expanded with 21 new indicators, including lip width and hair colour. AI was first launched in 1988 with the goal of creating theoretical tools that were already in use but had shortcomings. In order to simplify and edit images without the usage of human markers, mathematics (sometimes known as "linear algebra") was employed.

The first successful example of technical HFRs was reported in 1991 by Massachusetts Institute of Technology (MIT) researchers Alex Pentland and Matthew Turk. Eigenfaces employing Principal Component Analysis (PCA) for HFRs were used in (Turk and Pentland, 1991). In 1998, Défense Advanced Research Projects Agency (DARPA) created technological HFRs called FERET to inspire industry and academia to advance on this subject (Phillips, Wechsler, Huang and Rauss, 1998). This program made available to the world a large, difficult database consisting of 2400 image graphs for 850 individuals. Launched in 2005, the HFRs Grand Challenge (FRGC) [9] competition seeks to promote and create technological HFRs that complement current HFR initiatives. DL, a Machine Learning (ML) approach that uses artificial neural networks, accelerated everything in 2011. The machine chose points of comparison since it learns faster when given more images. In 2014, Facebook identified Deepface using its own algorithm [10]. Apple's latest updates included an HFRs application, which is now used in banking and retail. Selfie Pay, an HFRs framework for online transactions, was created by Mastercard.

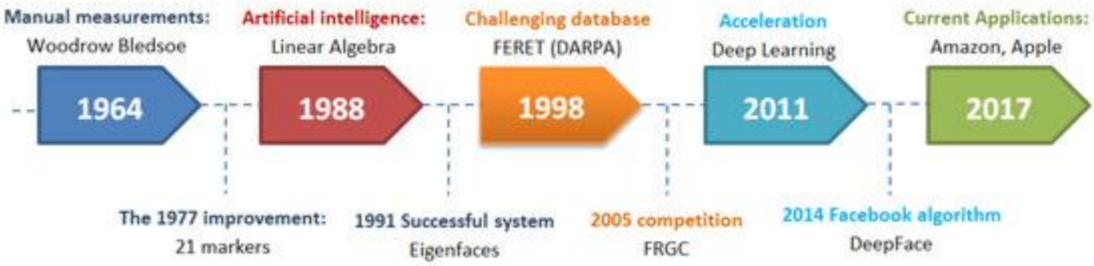


Fig. 1 - History of hfrs

The comparison procedure has been expedited and judicial staffs have become more efficient due to Technological HFRs (Li and Jain, 2011). AI-powered automated HFRs are computer vision technologies that recognize or authenticate people by their distinct facial traits. First, AI algorithms determine whether and where human faces are present and the system takes out distinctive facial traits and turns them into a numerical representation, which is frequently referred to as a "facial template" or "faceprint." This entails calculating the separations between important features (such as the mouth, nose, and eyes) and examining the forms of facial contours and jawlines. These features are encoded into comparison-ready representations, frequently as numerical data vectors. Subsequently, a database of recognized faces is matched to this facial template. The matching procedure is carried out by AI algorithms, which assess if the captured face and any stored profiles are highly similar. On the other hand, modern HFRs, which are linked to AI methods, allow someone to be recognized by his face or confirmed to be who he says he is. For its defenders, HFRs provide secure, quick, and accurate identification to guard against frauds. Major advancements in HFRs have been made possible by AI technology (Morder-Intelligence, 2020). Early on, the primary focus of study was on HFRs in controlled settings, where straightforward classical methods produced outstanding results. Deep learning (Guo and Zhang, 2019) has grown in popularity under unconstrained circumstances, where researchers are currently focusing. Despite having matured, existing machine learning and recognition algorithms can only meet the demands of real-world applications (Kortli, Jridi, Al Falou and Atri, 2020). For example, there are still a number of challenges to overcome when attempting to identify facial images collected in uncontrolled situations like partial occlusions, camera movements, lighting variations, postures, and facial expressions. Hence, utilizing the Yale Faces dataset, this work suggests the AIBRF schema for automatic HFR which analyses and processes facial data using DL techniques. Following this introductory section, the problem is defined in section 2 followed by review of related literature as section3. Section 4 details the methodology of AIBRF schema followed by its implementation results in section 5. This paper concludes with future scope in section 6.

Definition of the Problem: Technological HFRs are far from perfect despite their wide usages. Their efficacy may be weakened by a number of obstacles including variations, in facial appearances, poses, illuminations and ageing. Occlusions, expressions and surgical changes in faces also can undermine the purpose. Blurred or low-resolution images are also defined issues in HFRs. Human faces can be greatly impacted by changes in head rotations, viewing angles and lighting variations as they change facial appearances making their recognitions challenging. Accuracy of recognitions are impacted by changes in facial features brought on by ageing, weight fluctuations, haircuts, or makeups. Important facial features may be obscured by items such as masks, spectacles, or scarves that partially hide the face. Facial expressions have the power to change how facial characteristics are visualized. Plastic surgery on faces can also drastically change facial features, making it challenging to recognize them. Both humans and technology struggle to distinguish between people with similar face traits. Accurate feature extraction may be hampered by grainy or low-resolution images, which are frequently from security cameras. Important facial features may be hard to see in out-of-focus images. Sensitive biometric data is collected and stored by HFRss, which raises worries about data breaches and illegal spying. Certain groups may be unfairly or inaccurately identified by HFRs algorithms due to bias based on age, gender, or ethnicity. Concerns regarding possible abuse for monitoring and surveillance are raised by the extensive use of technological HFRs. The public's approval of technological HFRs may be impacted by privacy concerns and their misuse. Other Challenges include data breaches involving compromised biometric information which may result in long-term security problems because biometric information is more difficult to update than passwords, Adversarial attacks by skilled attackers who can trick recognition systems with methods like deepfakes. Furthermore, there are a number of difficulties facing technological HFRs, such as concerns about security, privacy, and accuracy. Low-quality images, different poses, and aging-related or other appearance changes might be problematic for these systems. Concerns have also been raised about possible prejudice, data misuse, and the effect on personal privacy. Additional concerns include environmental elements such as performance of HFRs devices can be impacted by variations in lighting, shadows, and other environmental elements. Motion and blur similar to HFRs algorithms may not be able to match the subtleties of human perception, such as identifying subtle facial expressions or differences in look, and the system may have trouble correctly identifying a person due to moving subjects or hazy images. Continuous research and development is necessary to address these issues, with an emphasis on enhancing accuracy, guaranteeing equity, and defining precise ethical standards and laws for the application of technological HFRs. Hence this work proposes AIBRF to cover these deficiencies in HFRs. The schema identifies faces using DL techniques. The schema is trained on the Yale Face dataset and achieves 99% accuracy in HRFs.

2. RELATED WORK

This review of related works aims to analyse the strengths, limits, and opportunities for development in automated HFRs where facial detections are the first step, followed by further procedures. Several studies have examined into the application of ML and DL techniques in HFRs. Algorithmic HFRs differ in terms of performance, computational efficiency, resilience, and application. (De Carrera and Marques, 2010). This study examined a variety of approaches, such as statistical, geometric, and pattern-based approaches, and came to the conclusion that HFRs were still difficult to solve even with technological advances Algorithms faced typical difficulties due to factors like speech presentation, image capture, and variations in illumination. Although there had been advancements, the assessment noted that further study was needed in areas like emotion and image-based recognition. The goal of the review by Kaur, Krishan, Sharma and Kanchan (2020) was to briefly analyse approaches used in technological HFRs, taking into account their advantages, disadvantages, and potential uses. In their extensive literature review, the authors describe the many tasks and algorithms employed in the field, as well as the evolution of HFRs from their inception in the 1960s. The work of Cavazos, Phillips, Castillo and O'Toole (2020) examined racial groups—East Asians and Whites—and the sources of bias. The authors compared three deep convolutional neural networks (DCNNs) against a previous generation approach, while Adjabi, Ouahabi, Benzaoui and Taleb-Ahmed (2020) reported that 2D HFRs under controlled conditions were successful. Despite recent advancements, the study discovered that HFRs are limited in uncontrolled environments where variations in light, space, and objects affect their effectiveness. Additionally, it was determined that privacy and individual freedom are ethical concerns that must be taken into account.

A thorough review of DL techniques for HFRs, including a variety of strategies and developments in the area, was generated by Bao, Hu, Chen and Sun (2018). Based on a careful review of the literature, they categorized different models and applications, highlighting significant developments and trends. Although the survey gave scholars valuable information, it lacked a comprehensive performance comparison of the several approaches discussed. Alameda-Pineda, Ricci and Sebe (2016) examined CNN-based systems specifically for the verification of masked faces. Evaluating the performance of convolutional neural networks in the presence of partially obscured faces was the aim. Using pre-existing datasets, the authors assessed how well different CNN designs performed when obscured. The focus on occlusion offered interesting insights about CNNs' resilience in such situations, even though it did not correspond with the widespread use of HFRs. It suggested more research with different occlusion levels.

Wayman, Jain, Maltoni and Maio (2005) conducted a complete analysis of biometric recognition systems. The study's goal was to educate people about biometric ideas and uses, particularly in HFR cases. The authors provided some fundamental information regarding biometric identification systems by integrating broad theory, real-world applications, and case studies. Alsmadi (2016) examined HFRs in the context of media conflicts and made recommendations for increasing the robustness of recognition systems. Although the study was fascinating, it may have been less useful in practice because it did not provide detailed solutions to well-known subjects.

The study by Chai and Wu (2017) aimed to gain a better understanding of possible applications of HFRs by examining several DL algorithms used on faces. They organized and analyzed a number of initiatives in order to do a thorough analysis of the most recent research. The paper highlighted significant developments and the possibility for more study, even though certain recent studies could not be discussed because of how quickly the field is developing. Chen, Chen, Liu and Tang (2019) proposed a DL-based innovative face technique. Their objective was to develop a workable algorithm that would increase HFR tasks' accuracy. The novel method was evaluated against existing algorithms that used DL techniques and demonstrated better performance indicators using a benchmark dataset. However, the performance of the method might have varied based on special circumstances or the type of data.

An overview of DL-based HFRs was provided by Chiachia, Sgouropoulos and Pitas (2018), but because of their wide scope, some important issues might not have received enough attention. Ding, Xu and Tao (2017) discussed different DL techniques using HFRs. In a number of approaches, the researchers aimed to enhance voice recognition. Their outcomes cleared the path for the development of technical instruction by demonstrating its value for professional speech recognition. However, employing many perspectives could make implementation challenging in real-world applications where such data might not be easily accessible.

The work of Guo, Zhang, Hu, He and Gao (2016) examined DL-based HFRs approaches. The authors wanted to give readers an overview of the growth and advancement of the sector. Through a survey and categorization of the current literature, they were able to identify patterns and obstacles in DL applications that will inform future research. However, some of the recent advancements might have been lost because the area was so dynamic. A novel approach for HFRs was explained by Han, Jain and Learned-Miller (2017), who contrasted single images with collections of similar image graphs for solving various shape and expression challenges in order to increase recognition accuracy. They suggested a matching recognition architecture that considers the matching scores in order to enhance the recognition process. It offered a fresh viewpoint on the use of numerous images for identification and had great promise for surpassing existing techniques. The fact that each individual has a sizable image collection—which may not always be accessible in practical applications—was a crucial factor.

The work by Huang, Mattar, Berg and Learned-Miller (2008) presented the “Labeled Faces in the Wild” (LFW) dataset for facilitating the learning of HFRs in an unrestricted setting. Their goal was to supply information for use in real-world HFRs. Among the more than 13,000 images gathered from the Internet, the dataset reveals a novel trend. The LFW dataset has greatly advanced the field of HFRs and has become a benchmark in the industry. Despite the vast amount of data, it might not have included all the differences and complications that might arise in practical applications. In order to determine the optimal CNN design for HFRs, a comparative analysis of CNNs for HFRs was conducted by Huang, Hong, Chen and Shang (2019), where potentials for therapy combinations were examined for better results.

The work of Smith and Doe (2020) offered a fundamental framework while discussing the theoretical underpinnings and applications of support vector machines (SVMs). With the use of case studies and actual situations, they aimed to provide the audience with a conceptual grasp of the fundamentals of SVMs. This book provided a thorough overview of SVM and aided scholars and practitioners in making the most of this method. It was hard to talk about the most recent advancements in support vector machine research and applications without such a fundamental idea.

Kalayeh, Basaru and Murthy (2019) compiled a number of different DL methodologies. The authors methodically examined and categorized the approaches while taking into account industry trends and difficulties. The findings of this study were intended to direct future research paths for DL applications in HFRs, though it might not have included the most recent advancements in this dynamic sector. Kaur and Singh (2019) presented a thorough analysis of DL methods for autonomous facial expression recognition (FER). Among their contributions were recommendations for future research directions and an overview of noteworthy advancements in DL applications for FER.

Khan, Hayat, Bennamoun, Sohel and Togneri (2017) proposed a low-cost technique for obtaining deep characteristics from human populations. Their study concentrated on resolving issues that arise during DL model training due to inaccurate data. They offered inexpensive training for worker change in order to successfully address gender inequity. Their contributions showed that the novel method may use minimal datasets to attain great performance in clusters. However, their techniques might not work in other areas because they were dependent on a particular database. Li, Chen, Liu and Gao (2020) suggested an approach to deep neural networks that uses multiple layers with the goal of enhancing FER. They created a DL method to extract information from facial images by employing a categorization scheme. One of their accomplishments was surpassing conventional techniques in terms of improvement, proving the efficacy of multi-scale hierarchical designs. However, this model was costly, and its performance varied depending on the dataset.

Li, Wang, Tan and Huang (2018) introduced a novel technique for HFRs that used DCNNs with many connections to improve the accuracy of identifying different feature combinations, such as shape, texture, and color. This strategy demonstrated its applicability for bioavailability and safety validation by doing well in validation tests. However, deep CNNs were limited in their application when resources were constrained due to their high processing power requirements. Future studies should concentrate on refining the model and assessing its performance in diverse real-world scenarios.

DL applications to HFRs were examined by Reddy, Mohanty and Sahoo (2019), who demonstrated significant improvements in performance and accuracy. Practitioners interested in learning more about the current status of technological HFRs found this review to be helpful. They do point out, however, that this kind of review might not be enough to explore the difficulties and restrictions of some methods, which could complicate the topic. Seetharam and Mohanty (2019) examined a successful ML-based HFR and showed increases in accuracy. Their method demonstrated that computation for quick applications is feasible, which made it noteworthy. The study did not, however, particularly address the algorithms' shortcomings, which might have had an impact on their scalability and ease of use in various contexts.

The work of Wang, Gong, Zhu and Zhou (2020) gave a summary of DL and HFRs, outlining several strategies and real-world uses. Researchers and practitioners benefited from the depth of the research, but it might not have adequately addressed the difficulties and constraints faced in global environments. Wu, Liu, Yang and Pan (2020) suggested a novel DL technique that enhanced image downsampling's resilience and could be applied to face recognition in noisy images. Although their method showed a lot of potential, it might not have worked well in unpublished contexts because of its dependency on large training sets. The capacity to integrate support vector machines (SVM) and principal component analysis (PCA) for HFRs was investigated by Faruqe and Hasan (2009). Their findings showed that the measurement was robust, but the method's efficacy might have been constrained by its reliance on a number of factors, including viewing angle and lighting.

To help with HFRs, Tang, Lim, Chang and Tao (2009) created the Ashape modeler to manage brightness variations. This strategy showed promise, but because of its intricacy, it might have been difficult to implement and may have required more upkeep. Gross, Matthews and Baker (2017) investigated the use of eigenlight fields to enhance HFRs in various positions. Although their novel modeling approaches were outstanding, their intricacy hindered computational efficiency and made them hard to use in practical settings.

Rowley, Baluja and Kanade (1998) introduced a method for recognizing straight frontal faces in images that was based on neural networks. In order to improve performance, several networks worked together to analyze small visual windows utilizing retinally linked neural networks. The collection of non-facial images was streamlined by using a straightforward training method for matching positive face samples with a grunt algorithm to dynamically generate poor instances.

Part-based and holistic processes of individual differences in face processing ability (FPA) were detailed by Audette et al. (2025). Multiple linear regression analysis was used to anticipate the links between participants' FPA, part-based efficiency, and holistic processing in order to explain the variability in FPA. Sixty-four people with normal or corrected-to-normal vision, aged 18–30, participated in the study. A psychophysical paradigm that assessed the ability to distinguish between individual face features and those in combination was used, followed by standardized face and object recognition tests such as the Glasgow Face Matching Test (GFMT) and Cambridge Face Memory Test (CFMT). Multiple linear regressions and correlations were used in the data analysis process.

In order to improve the accuracy and efficiency of HFRs, Fazilova et al. (2024) concentrated on creating recognition algorithms that examined the relationships between a face's local features. Their methodology involved face detection, image processing, segmentation of local regions (mouth, nose, eyes), feature extraction, and database comparison. However, further testing on diverse datasets was required to enhance the algorithms' applicability, which also depended on the quality of the chosen local characteristics.

Enhancing HFR algorithms to handle environmental restrictions such as occlusions and varied facial expressions was the aim of Mirzaeva et al. (2024). They tested the effectiveness of a DL algorithm named FaceNet with an enhanced PCA technique called HE-GC-DWT-PCA/SVD. While recognition rates were determined by PCA-based feature extractions, these were limited by the computational complexity of PCA.

The majority of the related works showcase a wide range of innovative techniques and discoveries in image processing, yet remain unconnected to the unique challenges and advancements in HFR algorithms. This discrepancy highlights the significance of conducting targeted research that focuses on the nuances of HFRs.

3. METHODOLOGY

HFRs are biometric technologies that use facial traits to identify people. They operate by examining and charting distinctive features including the separation of eyes, nose shape, and jawline contours. After that, this data is transformed into a digital representation, which is frequently referred to as a facial template. The initial stage of automated HFRs is face recognition. It typically establishes whether a face or faces are present in an image. If it does, its purpose is to locate one or more faces in the image (Viola and Jones, 2004). There is a high demand for HFRs in many real-world scenarios, such as crime scenes, security, and attendance checks. Early research employed artificial features to train classifiers, such as the cascade face detector (Viola and Jones, 2004), where Haar-like features were introduced and detectors were trained using AdaBoost. However, the detector's performance declined dramatically in realistic scenarios or when evaluating complex facial variations. Deformable part models (Benzaoui, Bourouba, and Boukrouche, 2012) were also introduced for HFRs in addition to this cascade technique. The applications of CNNs and deep learning in diverse domains such as NLP (Collobert et al., 2011), speech recognition (Graves and Schmidhuber, 2010), and object recognition (Krizhevsky, Sutskever, and Hinton, 2012) motivated the proposal of AIBRF based on Multi-Task Cascaded Convolutional Networks (MTCNNs) for HFRs. The suggested AIBRF schema uses the Yale faces images database to learn and encompasses six stages namely EDA, Pre-processing, feature Extraction/Building the Dataset, Test/Train Splits, Building the AIBRF model and finally using it for Predictions after training. Fig. 2 displays a sample image read by AIBRF from disk.

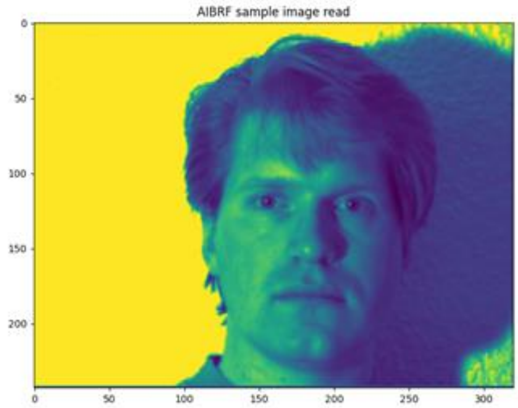


Fig. 2. aibrf sample image read

Exploratory Data Analysis (EDA) is a crucial initial step for scientists working in disciplines including biology, environmental science, public health, and data science to understand complicated information. EDA is a technique that summarizes the key features of data, frequently with the use of visual aids, in order to comprehend structure, identify patterns and anomalies, and verify hypotheses. EDA employs visualization, which is the process of visually inspecting data using plots and charts. For example, bar charts are used to display frequency for categorical variables. Heatmaps use color intensity and statistical analysis to illustrate relationships between numerous variables, scatter plots to demonstrate the relationship between two variables, and histograms to show the distribution of a single variable. In order to comprehend data dispersion and central tendency, summaries produce summary statistics such as mean, median, variance, and standard deviation. Prior to formal modeling or analysis, it entails a cycle of data cleansing, visualization, feature engineering, and hypothesis testing to obtain insights that can assist guide decisions and create better models. There are two primary types of image detectors: those used in imaging and imagegraphy to take or recreate images (such as CCD and CMOS sensors) and AI-powered detectors that distinguish between artificial intelligence-generated and human-generated content, frequently offering an authenticity confidence level. The latter are quickly evolving, but not always entirely accurate, methods to counteract false information and phony images by identifying minute patterns and artifacts left by AI generators, while the former are essential to how we see and record the world. In addition to differentiating between actual (human-made) and AI-generated images, AI image detectors can occasionally identify the particular AI model being utilized.To identify distinctions that are frequently imperceptible to the human sight, such as patterns and artifacts exclusive to AI creation, they are trained on enormous datasets of both human and AI-generated images. Rectangular outlines known as facial limits or bounding boxes indicate the position and dimensions of an identified face inside an image or video frame. These boxes are produced by face identification algorithms, which either pinpoint the exact location of the face to be isolated or, in the case of more intricate processes, locate important facial features inside the bounding box using facial landmark detection. Preprocessing image data for ML entails converting unprocessed images into a format that can be used for inference and model training. The goals of this procedure are to increase model performance, standardize data, and improve image quality. Resizing and cropping are important methods since images frequently have different dimensions. In Normalization and Standardization, Images' pixel values might vary greatly. Training is stabilized and convergence is improved by normalizing or standardizing these values (e.g., scaling to a range of 0-1 or standardizing to a mean of 0 and standard deviation of 1). Reduction of Noise Noise from a variety of sources, including as compression artifacts and sensor noise, can be present in images. Image clarity can be increased and noise can be decreased with methods like median filtering and Gaussian blur. Enhancement of Contrast (Feature distinction can be improved by adjusting the contrast of an image. One popular technique for this is histogram equalization. Although it is a distinct concept, data augmentation is frequently taken into consideration in conjunction with preprocessing. In order to increase the training dataset and enhance model generalization—especially in situations with limited data—it entails producing altered versions of pre-existing images (such as rotations, flips, shifts, and zooms). These preprocessing procedures should be conducted uniformly across training, validation, and testing datasets to guarantee that the model learns from and is assessed on data that has undergone the same changes. The particular methods selected are determined by the needs of the ML task as well as the characteristics of the picture data. The process of turning unprocessed data into a collection of fresh, insightful features that are better suited for ML models is known as feature extraction. Three phases of convolutional networks that can identify faces and landmark locations like the mouth, nose, and eyes make up the procedure. The overall architecture of AIBRF schema is depicted as Fig. 3.

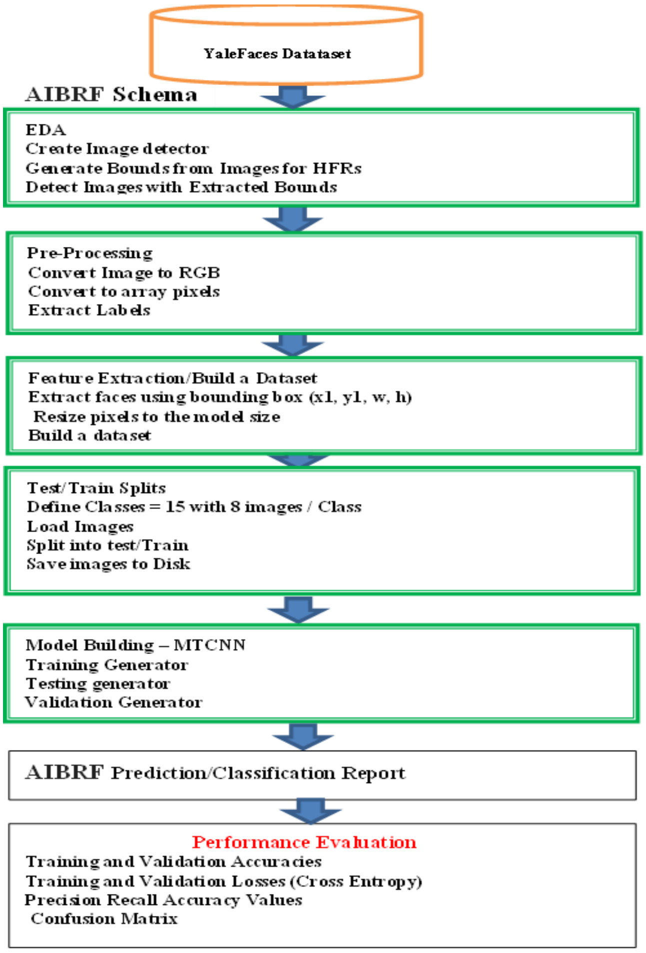


Fig. 3. Aibrf architecture

AIBRF uses MTCNN as a means of employing multi-task learning to combine the two tasks (alignment and recognition). In the initial phase, it generates candidate windows rapidly using a shallow CNN. Image are first resized to multiple scales for generating image pyramids, inputs for subsequent tri staged cascaded networkd (refer Fig. 4).

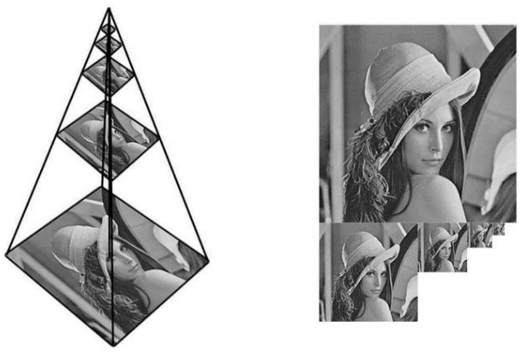


Fig. 4. Resized and Scales Input Images for Building Image Pyramids

Stage 1: Proposal Network (P-Net): The first stage is to build a fully convolutional network (FCN). A totally convolutional network varies from an FCN in that it does not include a dense layer in its architecture. This proposal network generates candidate windows as well as bounding box regression vectors. When the goal is to detect an object from a predefined class, such as faces, bounding box regression is a popular technique for forecasting box localization. Following the capture of the bounding box vectors, overlapping regions are joined using some refinement. All candidate windows that are refined to lower the number of candidates are the stage's final output. Fig. 5 displays a P-network.

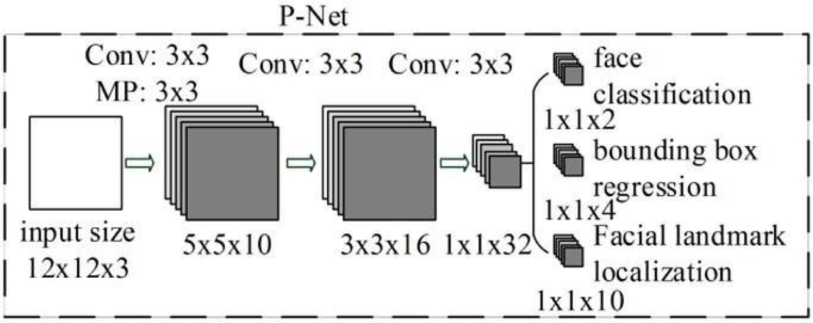


Fig. 5. p-net

Stage 2: Refine Network (R-Net): R-Net receives all of P-Net's candidates. The dense layer at the conclusion of the network architecture indicates that this network is a CNN rather than an FCN, as was the prior one. In addition to considerably lowering the number of candidates, the R-Net merges overlapping candidates using non-maximum suppression (NMS) and calibrates with bounding box regression. The R-Net Fig. 6 generates a 4-element vector that serves as the face's bounding box, a 10-element vector for facial landmark localization, and an output indicating if the input is a face.

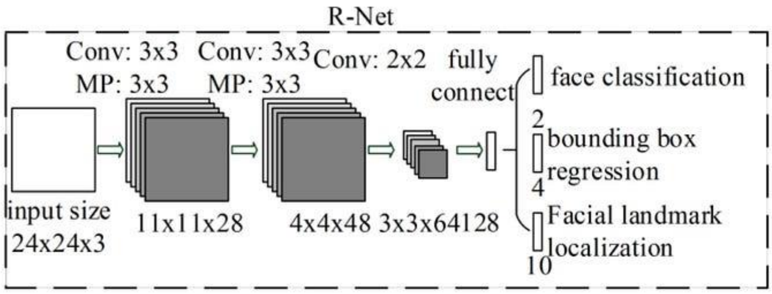


Fig. 6. r-net

Stage 3: Output Network (O-Net): This step (see Fig. 7) is comparable to the R-Net, but the output network's purpose is to produce a more comprehensive descriptions of faces and outputs locations of the five facial landmarks for the mouth, nose, and eyes.

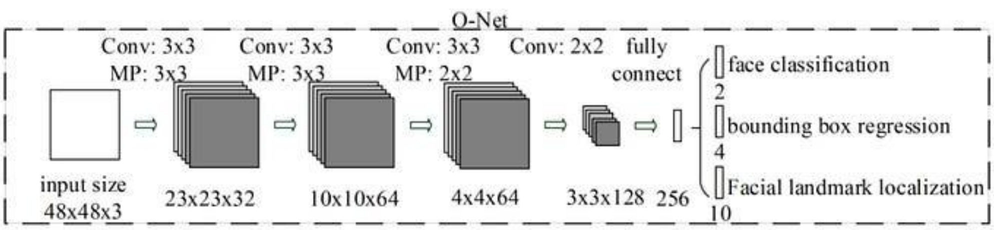


Fig. 7. o-net

Face/non-face classification, bounding box regression, and facial landmark localization are the three outputs that AIBRF seeks to provide. Face classifications are binary classification problems that employ the cross-entropy losses

Bounding box regressions concentrate on regression issues in which the euclidean loss determines offsets between candidates and closest ground truths for candidate windows. Localizations of facial landmarks that are developed as regressions utilizing Euclidean distance for losses are known as facial landmark localizations. Thus, the nose, left and right eyes, and the corners of the mouths are the landmarks**.**

4. RESULTS AND DISCUSSIONS

AIBRF utilized the Yale Faces Image Database, which includes 11 subjects: wink, sad, drowsy, astonished, pleased, left light, no glasses, normal, right light, center light, and spectacles. Each subject has 15 samples, totaling 165 picture samples. AIBRF is used by HFRs to identify or validate people based on their distinct facial traits. It processes and analyzes facial data by utilizing MTCNN. Images are first analyzed for the presence and placement of human faces, which entails looking for facial features like the mouth, nose, and eyes. Subsequently, AIBRF extracts unique facial features and converts them into numerical representations. Subsequentlyt, they are encoded into comparison-ready formats. After that, the framed templates are contrasted with database faces that are known to exist. AIBRF can continuously learn adapting to differences in illumination, angles, and facial expressions and enhance its accuracy as more data is supplied.The stage wise experimental results of AIBRF implemented in Python 3.9.5 on an AMD Athelon CPU with 4 GB of RAM, are detailed in this section.

AIBRF- EDA: AIBRF creates Image detectors and facial Bounds from Images for detections which use extracted Bounds. Image detectors are used as they indicate likehood of AI generated images (Confidence). Facial Bounds are generated by AIBRF after scanning images to identify presence of human faces. On detections, a rectangular box (the facial bound) with coordinates specifying its position and extent represented by (x, y, width, height) values are generated. The coordinates of the bounding boxes are are crucial for HFRs. Fig. 8 depicts the output of AIBRF's Image bound detections using Default Weights.

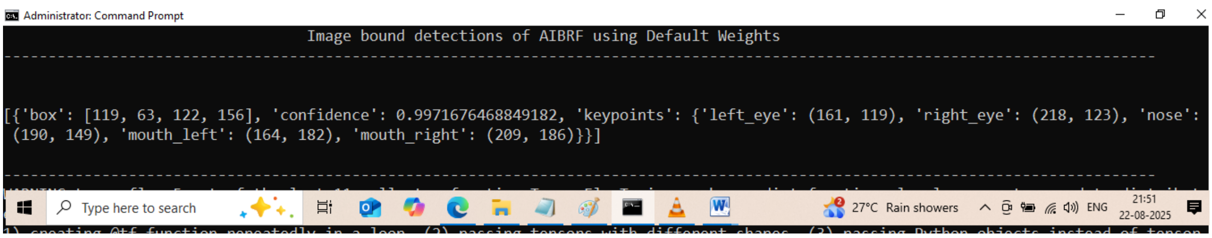


Fig. 8 . Image Bounds of Yale Faces

The values found were [{'box': [119, 63, 122, 156], 'confidence': 0.9971676468849182, 'keypoints': {'left_eye': (161, 119), 'right_eye': (218, 123), 'nose': (190, 149), 'mouth_left': (164, 182), 'mouth_right': (209, 186). These values are then used by AIBRF (Refer Fig. 9) to mark images and extract facial features.

AIBRF-Pre-Processing (Refer Fig. 9): AIBRF's pre-processing steps convert images to RGB for consistency, particularly when processing or analyzing many images in various color modes. The labels or subjects are also retrieved by AIBRF at this stage. For models using CNNs, resizing images to uniform sizes are essential to get consistent inputs. Additionally, cropping can be utilized to highlight particular areas of importance. Color Space Conversion: Images may be in RGB or grayscale, among other color spaces. Making the switch to a standard format is crucial. When color information is not essential, grayscaling can simplify computation.

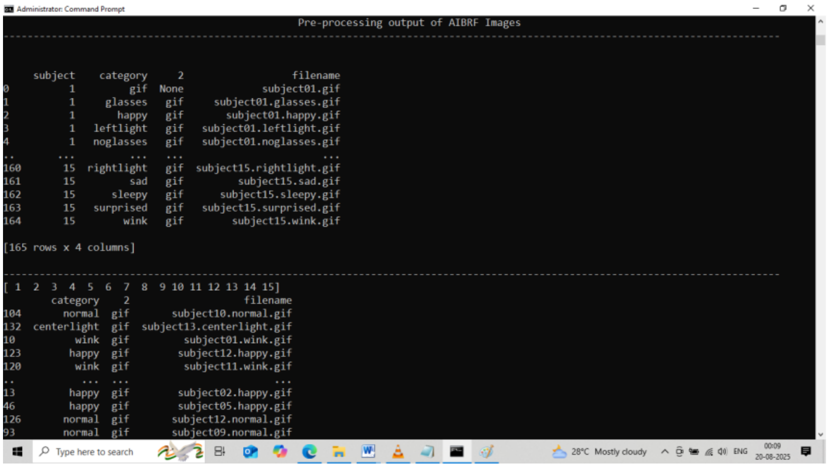


Fig. 9. Identification of Labels (Subjects)

AIBRF-feature Extraction: AIBRF schema uses bounding boxes (x1, y1, w, h) to extract facial parts. Facial Bounds is used to make it simple to remove faces from image backgrounds. Bounding boxes act as the Region of Interest (ROI) for the next stage, which is to identify particular important facial features like the mouth, nose, and eyes. AIBRF Image Bounds-based image marking for feature extractions is shown in Fig. 10.

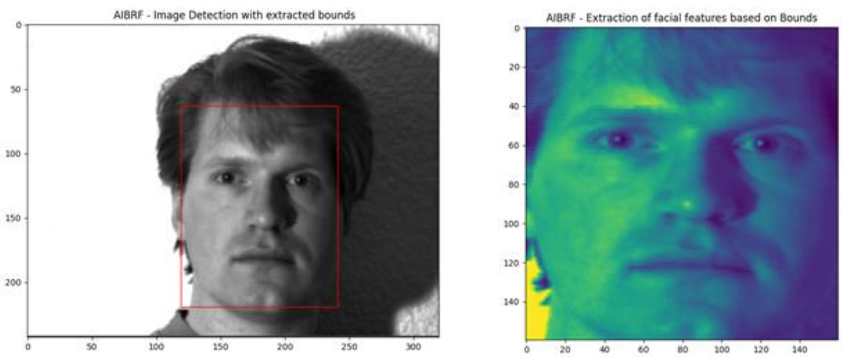


Fig. 10. AIBRF Image Bounds based image marking

Highly discriminative features unique to the possible item locations can be extracted using this region-based method. Bounding box annotations act as ground truth labels for object detection model training. Algorithms are trained to identify and extract discriminative characteristics from these labeled bounding box regions during feature extractions. This enables the model to link particular object classes and their locations to specified features. AIBRF automatically learns hierarchical characteristics from photos and develops new features to improve its performance. After extracting features from photos using bounding boxes, AIBRF uses the input images to create its own dataset of 160 by 160 pixel images of facial parts as depicted in Fig. 11.

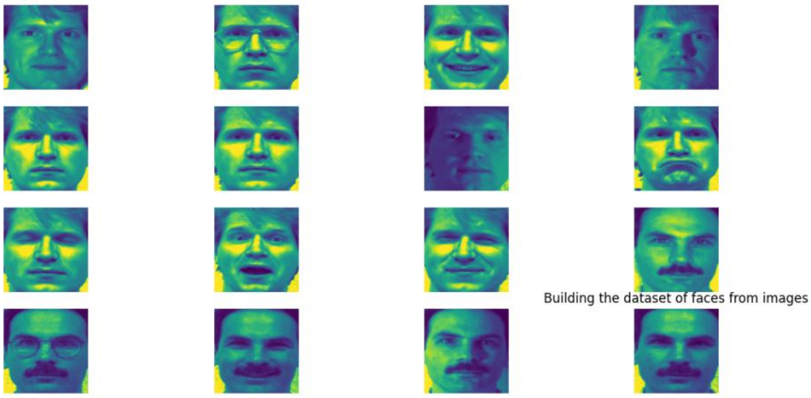


Fig. 11. AIBRF built dataset

AIBRF- Test/Train Splits: AIBRF, which learns to link particular feature patterns with recognized identities, is then trained using the features that were retrieved. The features of newly discovered, unidentified faces are taken out and compared to feature templates that have been stored. After that, the machine finds the closest match within a predetermined range. Faces that are displayed are compared to particular templates that have been stored and linked to identities that have been claimed. The identity is confirmed by the system by determining whether the faces match. Data overfits are avoided by these splits. Usually, a random shuffle is used to separate the data into two halves. The ML model is fitted or trained by the training set, which enables it to recognize relationships and patterns. The performance of the trained model is assessed using the Test set. The AIBRF Training/Testing divide is shown in Fig. 12.

AIBRF uses image counts to determine test/train divides. The standard ratio of 70% for training and 30% for testing is used by AIBRF. Predicted outputs and actual values are compared with the input features from the test set. AIBRF employs 15 classes (subjects) with eight images each class. Following feature extraction, the images are divided and stored on drives for future use. MTCNN serves as the foundation for AIBRF's model building, where training, testing, and validation generators are specified. The AIBRF Model is summarized in Fig. 13.

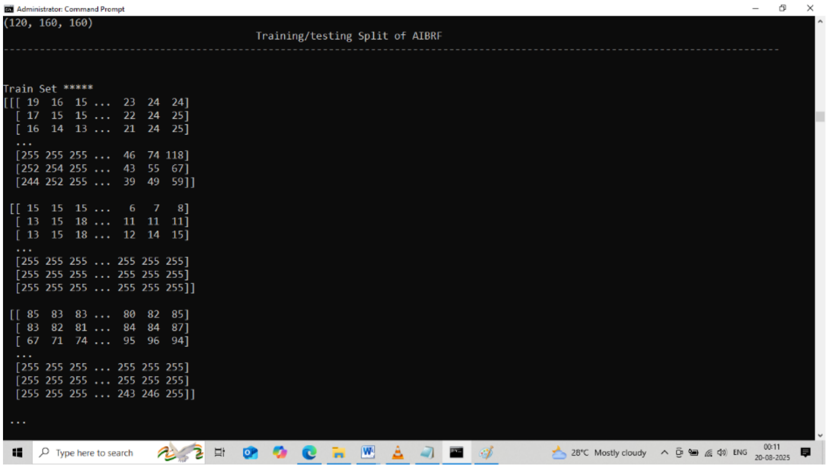


Fig. 12. Training/Testing split of AIBRF

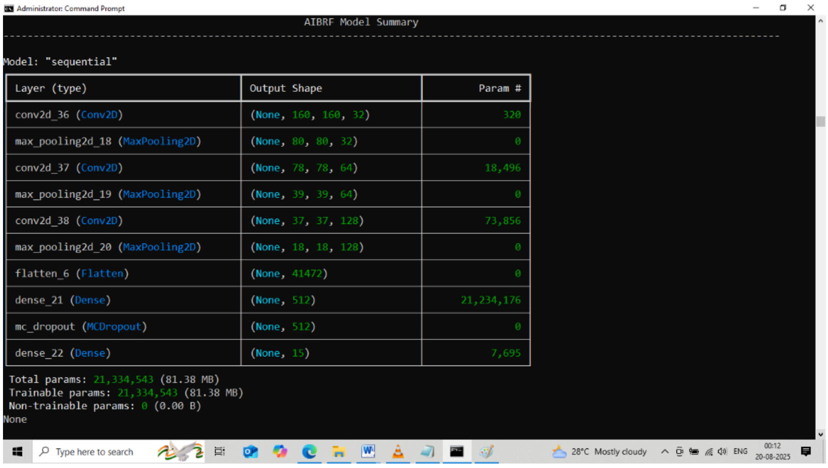


Fig. 13. aibrf dl model summary

Training data is fed into the algorithm, internal parameters are changed to optimize a loss function or minimize errors, and the model's mathematical representation is iteratively improved until the desired performance is attained. AIBRF learns to make mathematical connections between the target qualities (outputs) and the attributes (inputs) of the data. AIBRF's run for the test set where it predicts human faces is displayed in Fig. 14.

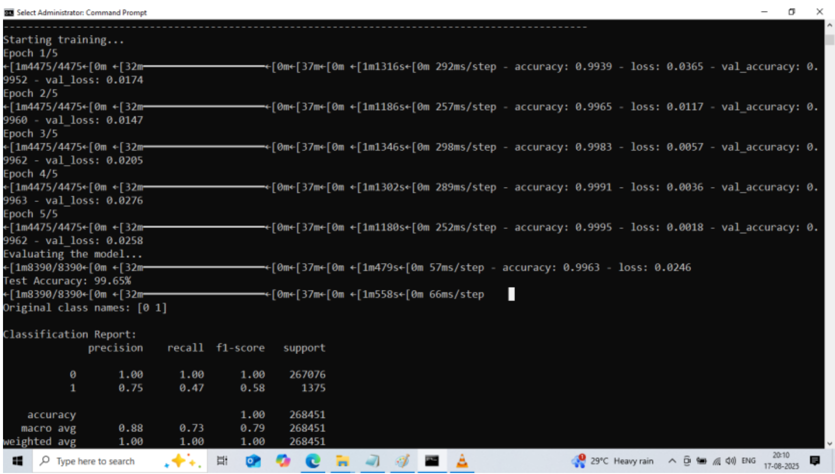
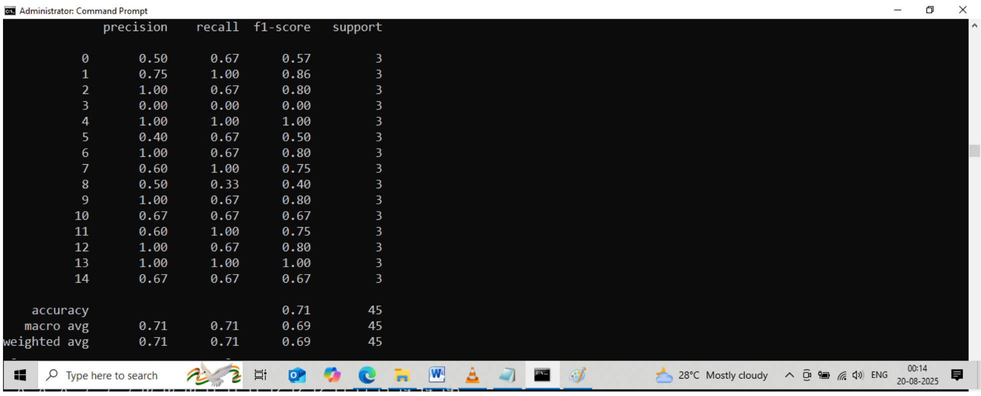


Fig. 14 – aibrf training/prediction

ML classification reports are metrics for performance evaluation that are specifically used to classification and prediction issues. They offer a thorough synopsis of how effectively categorization models predict various classes. These reports are produced by contrasting the model's predictions with the dataset's actual true labels. Preclasses and general averages are examples of metrics: The following metrics are employed by the AIBRF assessment metrics (see Fig. 15): precision, accuracy, support, F1-score, recall (sensitivity), macro average, and weighted average. Precision refers to the proportion of expected positive observations that are accurate. Recall (Sensitivity) refers to the proportion of correctly predicted positive observations compared to all observations in the class. F1-Scores represent harmonic mean of precision and recall values. It provides an unbiased evaluation of the model's performance, which is especially useful when the distribution of classes is not uniform. Support implies dataset's true instances for each class. Accuracy implies proportion of forecasts that are accurate, including real positives and negatives, compared to all projections. Macro Average represents the unweighted average of F1-score, recall, and precision across all classes. Weighted Average stands for the average of F1-score, precision, and recall across all courses, adjusted for class aid. Support represents the dataset's actual number of instances for each class.



	precision	recall	f1-score	support
0	0.50	0.67	0.57	3
1	0.75	1.00	0.86	3
2	1.00	0.67	0.80	3
3	0.00	0.00	0.00	3
4	1.00	1.00	1.00	3
5	0.40	0.67	0.50	3
6	1.00	0.67	0.80	3
7	0.60	1.00	0.75	3
8	0.50	0.33	0.40	3
9	1.00	0.67	0.80	3
10	0.67	0.67	0.67	3
11	0.60	1.00	0.75	3
12	1.00	0.67	0.80	3
13	1.00	1.00	1.00	3
14	0.67	0.67	0.67	3
accuracy			0.71	45
macro avg	0.71	0.71	0.69	45
weighted avg	0.71	0.71	0.69	45

Fig. 15. aibrf performance metrics

Weights are continuously changed during training in order to minimize a particular error or "loss" function that quantifies the difference between AIBRF's predictions and the labels of the training data.For the trained model to be useful in the real world, it must eventually be able to generalize from the known training data to produce precise predictions on new, unseen data. The Adobe figure makes it evident that AIBRF achieves a validation accuracy of 68.89% and a final maximum accuracy of 99.76%.

AIBRF Evaluations: Training and Validation Accuracies, and Training and Validation Losses are performance indicators used to evaluate AIBRF's performance. The Training Accuracy statistic measures a model's performance on the data used to train it. To effectively predict outputs for given training inputs, the model alters its internal parameters (weights and biases) during training to minimize a specified loss function. A high training accuracy indicates that the model has learned the patterns found in the training data. The validation accuracy statistic assesses a model's performance on a separate dataset, known as the validation set, that was not utilized for training. The validation set provides an objective assessment of the model's ability to generalize to new data. It aids in determining if the model has simply learnt the training data by heart (overfitting) or has acquired generalizable patterns. AIBRF's training and validation accuracy for HFRs is shown in Fig. 16.

Fig. 16. Training and Validation accuracies of AIBRF for hfrs

In order to detect and resolve problems like overfitting or underfitting and ultimately produce a more reliable and broadly applicable ML model, it is essential to track both training and validation accuracy throughout the model building process. Fig. 15 makes clear that the model has trained successfully and can generalize well to new data when both training and validation accuracy are high and near to one another. In ML, cross-entropy refers to the values of the cross-entropy loss function that are determined throughout the model training process on the training and validation datasets, respectively. One popular loss function for classification issues is cross-entropy. It measures the discrepancy between the actual probability distribution (one-hot encoded labels) and the model's projected probability distribution of classes. Because its predicted probabilities are closer to the true labels, a model with a lower cross-entropy value performs better. The cross-entropy computed on the model's training data is known as the training loss. The model's parameters are iteratively changed during training in an effort to reduce this loss and enhance the model's capacity to accurately categorize the training instances. The cross-entropy determined on a different dataset—the validation set—that isn't utilized for training is known as the validation loss. This loss aids in keeping an eye out for overfitting and offers an objective assessment of the model's performance on unseen data. Usually, training epochs or iterations are displayed against both training and validation losses. Effective learning of the model is indicated by a declining trend in both losses. Overfitting is suggested by a notable divergence in which the validation loss begins to rise while the training loss keeps declining. This suggests that while the model is retaining the training data, it is not generalizing to previously unknown data. AIBRF's learning loss curves are shown in Fig. 17. The fact that both losses decline simultaneously and with minimal variance suggests that the model has learned and made accurate predictions free from data overfits.

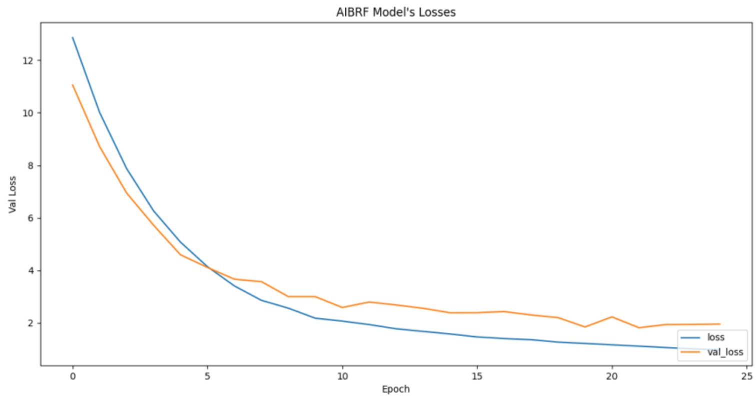


Fig. 17. AIBRF's training and Validation losses

5. CONCLUSION

Human faces are the most known biometric features, with numerous uses in everyday life. Since the invention of photography, both public and private organizations have saved facial images from membership cards, passports, or personal identification documents and used these collections as referential databases in investigations to compare and match the facial images of respondents such as victims, witnesses, or perpetrators. Furthermore, the widespread use of smartphones and digital cameras has made it simple to create facial image graphs, which can then be readily shared and uploaded via fast social networks. Thus, HFRs have been a fascinating and rapidly increasing subject of study. HFRs are used in real-time applications such as identification, access control, forensics, and human-computer interaction. Despite the fact that studies on HFRs have been proposed, there are still gaps in implementation. This work has proposed AI-based HRFs (AIBRF schema), implemented the schema with high accuracy rates in recognitions. It can be concluded that the suggested schema is implementable and can help in further development of automated HFRs. In future, AIBRF can be tried on other facial datasets and live faces for maintaining or improving predictions accuracies with reduced processing time.

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