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Innovative Integration of Convolutional Neural Networks for Enhanced Face Recognition

Abstract: The face Recognition technique is important in Computer Vision nowadays. The research study focuses on a Face Recognition system that uses deep learning to identify face photos. Face detection and categorization are carried out using various Convolutional neural network (CNN) models using deep learning methods. Prior research has mostly focused on either the ResNet or DenseNet-based CNN models. The current study combines ResNet and DenseNet to create a hybrid model. The suggested work aims to improve efficiency and accuracy. During the simulation's training and testing phases, categories are taken into account. The present study is centered on the Labeled Faces in the Wild (LFW) dataset. The photos go through an initial noise reduction procedure. Picture quality assessment involves considering measures like MSE, PSNR, and SSIM. Once the suggested model has completed training, it produces high-quality images. The suggested system includes the Innovative CNN approach framework, which combines DenseNet with a noise reduction approach, a segmentation mechanism, and a ResNet model based on CNN. Comparative research was performed to assess the precision of several filtered image collections using different convolutional neural network models. The simulation results show that the proposed model had higher performance and accuracy than traditional ResNet and DenseNet models.

Keywords: Face Recognition, Filtering, Segmentation, Deep Learning, Labeled Faces in the Wild (LFW).

I.INTRODUCTION

Computer algorithms have been used by facial recognition (FR) systems to recognize distinctive features that are present on the face of a person [1]. There is a comparison made between the feature that is given on faces in an FR database and the mathematical representation of such characteristics, such as the distance between the eyes or the curve of the chin [2]. During the process of evaluating identification papers, facial recognition is often used in conjunction with other biometric technologies to prevent identity theft and authentication fraud [3, 4]. Other biometric apps have been used to make a presence at educational and professional institutions, and face recognition is suitable for these applications in the modern period. The development of a face recognition system is a challenging and essential project to address security concerns. Different deep learning methods are used by several different face recognition systems. The CNN model was the primary focus of the research that was done before for face identification and categorization. The fact that there has been so little effort put into improving the quality of face images is one of the most significant problems with conventional processes. To proceed with the training operation, the image quality has to be increased [5].

The work that has been done about face recognition has been subject to many restrictions. These systems did not take into account the elements of performance and accuracy. Taking into consideration the traditional CNN model, it has been discovered that there is a need for more work to be done on the issues of overfitting and underfitting. In addition, there is a problem with the quality of the picture during the preprocessing stage. It is necessary to use noise reduction strategies to achieve the desired improvement in quality.

A. CNN Model for Face Recognition

Through the use of a CNN-based smart model in conjunction with an expanded facial image dataset, it is possible to extract face characteristics with a certain degree of success, resulting in an improvement in the accuracy of identification [6]. CNNs can generate a representation of a two-dimensional picture, which is one of the valuable features they possess. The upshot is that the model can learn the position of faces in a photograph as well as their size. CNN can recognize a person's face in an image after obtaining training on the subject matter. CNN's capacity to identify significant characteristics without the need for human interaction is one of the network's most significant capabilities. CNNs are a kind of artificial neural network (ANN) that was developed to handle pixel input in the context of image processing and identification. The input layer of a CNN is responsible for gathering visual data, whereas the hidden layer is responsible for carrying out internal tasks. This layer is responsible for producing output [7]. There have been several CNN models, each with its own unique set of characteristics. The following are the several kinds of CNN models:

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1) VGGNET: VGG-16 has been pre-trained on the enormous amount of photographs included in the ImageNet database that may be imported [8]. A popular deep Convolutional Neural Network (CNN) design is used by the Visual Geometry Group, and the name VGG alludes to the many layers that comprise this kind of architecture. When referring to VGG-16 and VGG-19, the term "deep" refers to the number of convolutional layers, that is, 16 and 19, respectively.

2) AlexNet: AlexNet is a framework that is considered to be state-of-the-art for any object recognition job. It has the potential to be used extensively in the area of artificial intelligence computer vision. This is because AlexNet was first developed as a tool for tackling problems in the field of computer vision. There is a possibility that shortly, AlexNet may take the place of CNNs as the solution of choice for photo tasks [9].

3) Inception: Image processing and object recognition are two applications that make use of the CNN model known as Inception V3. It had been conceived of as a module in the beginning. The Inception Module of a convolutional neural network (CNN) is a component of its image model that aims to simulate the most optimal local sparse structure [10]. In a nutshell, it empowers the utilization of several filter sizes inside a single image block, which may subsequently be concatenated and sent to the following layer.

4) GoogleNet: The beginnings of Google CNN technology have been subjected to two substantial changes [11]. GoogleNet is a convolutional neural network that has 22 layers and was built by Google Networks. There is the possibility of loading pre-trained models of the network that were developed using either the ImageNet [12] or Places365 datasets. The network can classify photographs into one thousand distinct categories, such as "keyboard," "mouse," "pencil," "animal," and thousands of others [13].

5) ResNet: It is used as the basis for many different computer vision applications. Twenty-five of these filters are used in ResNet50's layers. ResNet's most well-known contribution was that it made it possible to train extremely deep neural networks efficiently. This was accomplished by the use of skip connections and more than 150 layers, which enhanced the accuracy of the training process [8, 14].

6) DenseNet's levels: The convolution and pooling operations that make up the first layer of DenseNet are two of its components [15, 16]. Following this, there is a dense block, followed by a transition layer, then another dense block, followed by yet another transition layer, and finally, there is a classification layer, followed by a dense block. It is generally known that deeper networks have superior performance and are easier to train than their counterparts which are shallower and wider [17].

B. Noise Removal Filters

In the typical system, a method for noise reduction was not taken into consideration. The precision of the identification process that is carried out by machine learning is thus diminished [18]. Additionally, it is necessary to include noise removal filters that can remove noise from pictures during the preprocessing step. To reduce visual noise, filtering has been used. There are several applications for filters in the field of image processing [19], such as the reduction of noise, the interpolation of data, and the resampling of information [20]. In every image processing system, this is an essential component that must be included. Currently, available research on image processing takes into account the median, Gaussian, blur, and bilateral filters. The findings of this study indicate that the Gaussian filter yields superior results [21]. As a result of its characteristics, such as the Gaussian filter, Gaussian kernels provide less weight to pixels that are located farther out from the window's center. The reduction of harshness or noise in pictures is the fundamental purpose of this effect. Both the reduction of contrast and the smoothing out of edges may be accomplished separately by using the Gaussian filter [22]. One example of a function that is very sensitive to changes in its standard deviation is the Gaussian function. In a picture, noise may be removed and tiny features can be extracted using the Gaussian filtering technique [23].

C. Segmentation using HAAR Cascade

The Haar features travel across the picture in a window-sized pattern to compute and match features from different images. Considered to be an efficient classifier is the Haar cascade. Positive data points are those that contain a detected face, whereas negative data points do not include a face [24]. The data points are separated into two groups before being sorted. Given the pace at which they operate, Haar cascades are capable of achieving real-time performance. An algorithm that is capable of recognizing human faces in photographs, regardless of how small or far away they may be, is being developed. A haar-cascade detector may be trained to recognize a wide variety of objects, including human faces, automobiles, buildings, fruits, and more. When it comes to recognizing a face, it does so instantly [25]. Concurrently, CNN makes use of the convolutional process by propagating a convolution kernel, also known as a filter kernel, of a preset size from the product of the image's multiplication with the filter to the subsequent picture [26].

D. Paper Organization

Section 1 introduced traditional models using Convolutional Neural Networks (CNN) for face recognition and categorization. Section 2 discusses previously performed research on facial recognition, including the procedures and conclusions of the investigation. Section 3 contains both the recommended research approach and the proposed system design. Section 4 provides an example of noise reduction simulation, techniques, and accuracy metrics for a hybrid model. The paper concludes with a discussion of prospective future research in Section 5.

II.LITERATURE REVIEW

Many different types of studies have been conducted in the field of facial recognition, which involves the use of face identification and classification processes.

Using machine learning and deep learning techniques, K. Kavita et al. (2022) presented the concept of machine learning recognized for human faces. Tools such as Matlab and Python were investigated alongside these techniques. Facial expression analysis, face detection, face recognition, and age estimate were some of the approaches that were discussed in this paper. Furthermore, the paper centered its attention on the current and future directions of research in the field of face recognition systems [1]. P. T. Waghmare and colleagues (2021) conducted a literature review on facial recognition systems that are based on deep learning and are designed for broad use. This paper presented a complete biometric study of prior research on face recognition systems that are based on deep learning. Data analysis was carried out with the help of the Scopus database, and the information that was gathered was displayed with the assistance of a few different applications [2]. F. A revised version of LBP was merged with the deep CNN-learned abstract components of facial expression, as described by Kong et al. (2019). The model surpassed the competition by a margin of 91.28% when it was put through a head-to-head test [3]. S. By integrating an LBP algorithm with cutting-edge image-processing techniques such as contrast adjustment, bilateral filtering, histogram equalization, and picture blending, M. Bah et al. (2020) presented a revolutionary way to improve the performance of face recognition systems [4]. This method was developed to improve the overall performance of recognition systems. Fahad P. (2017), advocated researching the identification of faces. The real-time method that they offered was used to make intelligent decisions while the surveillance was being carried out [5].

Kirtiraj Kadam (2017) conducted a study on the attendance Monitoring System and published his findings. The processing of images was the primary focus of their study. A technique that is based on machine learning was used to carry out the categorization procedure [6]. Zhang (2018), focused on the process of automated segmentation. This study focuses on acute ischemic stroke caused by driving while intoxicated. The author used DenseNets that were completely convolutional in three dimensions [7]. Lu and Jiang (2018), proposed a novel CNN-based approach for low-resolution face recognition. This technique is a deep-coupled ResNet model. The DCR model that was proposed consistently performed better than the current state of the art on both the LFW dataset and the SCface dataset [8]. M. Z. Khan et al. (2019) published a deep unified model for face recognition that is built on CNN and edge computing. The performance was examined using a dataset that was available to the public. An algorithm was able to differentiate between the faces of thirty students and those of forty students based on a single shot, and the system was determined to be 97.9 percent accurate [9]. A comparison was made between feature-based face recognition and scalable sample learning for identification purposes by Zhu et al. (2019). IvS face recognition was accomplished via the presentation of a deep learning-based LBL technique. In addition, softmax was included in deep learning to make it possible to apply it to enormous datasets. An LBL analysis was carried out on an IvS face dataset that had more than 2 million distinct people [10].

Using deep convolutional neural networks, Almabdy et al. (2019) demonstrated algorithms for facial recognition. Throughout the preceding several years, the architectures of AlexNet and ResNet-50 have earned the highest possible results in ILSVRC. After conducting exhaustive testing on the ORL face, GTAV face, and FEI face datasets, it was discovered that the classification rates had improved. With an accuracy of 94%-100%, the model outperforms the majority of models that are considered to be state-of-the-art [11]. It is possible to recover characteristics from flawed face data by using A. The capacity of CNNs was revealed by Elmahmudi et al. (2019) via the use of the VGGF model. To determine the recognition rates of the model, cosine similarity and linear support vector machine classifiers were applied. Predictions were produced by using the information from both the FEI and the LFW [12]. Mohammed et al. (2023) This paper proposed a resampling-free PF approach that leverages the incoming observation in the particle sampling process and evaluated accuracy and computational complexity [13]. Lodhi et al. (2020) proposed an architecture, that used four different object recognition datasets. These datasets were CIFAR-10, CIFAR-100, SVHN, and ImageNet. Based on the results of the experiments, it was found that Multipath-DenseNet performed much better than its predecessor, DenseNet [14]. Sharma et al. (2019) developed a framework that was built on the sequential deep learning technique. Deep features were created by the model to help extract and refine the voxels that were rebuilt. We used the support vector machine (SVM) to analyze the attributes [15].

X. Han (2020) induced an example of image recognition research carried out by. The researchers used a method that was based on ResNet and transfer learning in this investigation [16]. In the subsequent work that Ke et al. (2020) concentrated on developing a self-constrained three-dimensional DenseNet model. Nasopharyngeal cancer, as well as the automated diagnosis and segmentation of this illness, are the primary topics of investigation in this work. For this investigation, magnetic resonance imaging was used [17]. Khawla Alhanaee et al. (2021) suggested a deep learning CNN-based facial recognition attendance system. It was found that the validation accuracy for the three networks that were employed varied from 98.33% to 93.33% to 100%. The implementation of the recommended technique into the attendance and security door access systems of a large number of firms might potentially serve to their advantage [18]. The research conducted by Said et al. (2021) focuses on the study of facial expressions via the application of deep learning and high-resolution photographs to interpret human emotions. A patch cropper and a CNN were the two stages that were suggested by the FS-CNNs. The first step consisted of the detection of faces, and the second phase consisted of the use of the clipped face [19]. Chowdary et al. (2021) developed software for human-computer interaction that was based on deep learning and was able to recognize facial expressions of emotion. Frameworks such as Resnet50, vgg19, Inception V3, and Mobile Net were used to train the pre-trained networks. It was decided to delete the completely linked layers of the pre-trained ConvNets and replace them with their custom-built layers that were scaled to correspond with the instruction set of the job. In conclusion, the only thing that was necessary throughout the training was to make adjustments to the weight of the additional layers [20]. The proposed method makes use of the Viola-Jones face detector to locate human faces in a picture, followed by a CNN that had been specifically trained and optimized for DIFR [20] to assign labels to the detected faces. Junaid Khan et al. (2021) developed a completely automated and highly effective convolutional architecture for disguise-invariant face detection. This architecture was created by utilizing noise-based data augmentation and deep transfer learning [21].

During the research conducted by Pratama et al. (2021), the CNN design known as ResNet-50 was used for face recognition. Various configurations of ResNet's primary parameters were put through a series of tests to see how effective they were. An accuracy of 99% was attained by the best model, which was achieved after being evaluated with 22 distinct configurations [22]. Sunitha et al. (2022) conducted a study that examined the identification and classification of face pictures based on ethnicity using clever deep-learning software. It was applied in the process of feature reduction. Since principal component analysis (PCA) is capable of effectively overcoming the "curse of dimensionality," which occurs when the recovered features are excessively dimensional [23]. Several different methods were used by Rehmat Ullah et al. (2022) to achieve remarkable accuracy using CNN. The performance was evaluated using KNN, decision trees, random forest, and CNN before being compared to CNN. An alternative setting was used using a real-time picture collection of 40K resolution. Last but not least, the system was able to detect faces with an accuracy of more than 90 percent in the shortest amount of time possible [24]. In their assessment of the classification study for recognized human faces using an augmented GoogleNet, Zhigang Yu and colleagues (2022) looked at the research. A recall rate of 0.97 and an accuracy of 0.98 were reached by the network, making it the platform with the greatest performance [25].

Anwarul et al. (2023) proposed a hyperparameter-optimized hybrid ensemble CNN for face recognition. Through the application of progressive training, the model achieved a significant improvement in recognition accuracy. The model obtained results that were the best in its class. The HE-CNN model that was presented was able to attain an accuracy of 99.35, 91.58, and 95%, respectively, when applied to the LFW dataset, the cross-pose LFW dataset, and the custom-built dataset [26]. Autism spectrum disorder was first described by F. Rabbi in 2023. They decided to address the problem of autism by constructing an image classification system for early diagnosis. They used transfer learning with VGG 19, inception V3, and DenseNet 201 to accomplish this goal. The photo dataset was used in combination with deep learning techniques by the researchers. A system that employs facial expressions as a proxy for autism was one of the strategies that they sought to build [27].

III.PROPOSED WORK

The main goal of this work is to create a Face Recognition system that can analyze digital photographs of people's faces using deep learning technology. To carry out face recognition and classification employing a technique that is based on deep learning, a great number of conventional CNN models are now being investigated. In traditional research, CNN models that are based on ResNet or DenseNet have been seen and investigated. Through the use of an integration of ResNet and DenseNet, the novel approach that has been suggested can deliver improved accuracy and performance throughout the classification process. The simulation work takes into consideration both binary and categorical classes throughout the whole of the training and testing stages of the model. Before implementing a hybrid CNN model that is based on ResNet and DenseNet, the current work takes into consideration scaling and picture filtering. In the course of research activities, the difficulties that are associated with conventional procedures, such as disregarding the quality of face images, are taken into account.

A. Proposed Research Methodology

Enhancing the image quality before the training operation has been the primary focus of the study effort that has been recommended. In the current research endeavor, the LFW dataset is taken into consideration. In this dataset, images are initially processed by a noise reduction mechanism that utilizes a variety of noise removal techniques, such as median, blur, bilateral, and Gaussian filters. The researchers concluded that Gaussian filters produced superior results in comparison to other filters. For this reason, a Gaussian filter is used during the preprocessing step, before the segmentation phase, to enhance the overall quality of the picture. In the next step, an evaluation of the picture quality is carried out, with MSE, PSNR, and SSIM. Mean Squared Error is often used in regression tasks to predict continuous data. MSE (Mean squared error ratio), calculates the mean of the squared discrepancies between the projected values and the actual target values. The formula for mean squared error is illustrated in Eq.1.

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2 \quad (1)$$

where m is the total number of rows of picture pixels, n is the image's column count f is the original image's matrix data g is the matrix information of our deteriorating picture.

The PSNR (Peak Signal to Noise Ratio) metric calculates how much noise detracts from a signal and the formula given in Eq. 2

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \quad (2)$$

where MAXf is the highest possible signal value in our reference "excellent" picture.
When calculating the SSIM (Structure Similarity Index Measures) index, a single image is used to generate some distinct window sizes simultaneously. When calculating the distance that separates two windows of the same size, we make use of the formula that may be expressed in Equation 3.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\mu_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (3)$$

where μ is the Pixel sample mean σ is Variance C is the Variables to stabilize the division with a weak denominator

In the next step, high-quality pictures are sent to a suggested novel approach, which is derived from the ResNet and DenseNet models for its foundation. The fundamental objective of the work that is being done using simulations is to assess the level of success that is obtained by different CNN models by making use of a range of filtered image sets.

B. Algorithm for Proposed Work

The suggested work includes a unique algorithm that outlines the process of evaluating the quality of photos in a step-by-step manner. Picture I should be used as input for the procedure. It is necessary to do the preprocessing step before carrying out the simulation using the novel approach model that has been presented. This is the order of the steps:

1. Input image I
2. Resize image I and get RI
3. Apply noise removal mechanisms on NRI
4. Get the Mean squared error ratio by Eq. 1
5. Get peak-sensitive noise ratios with the formula given in Eq. 2
6. Find the SSIM from the image expressed in Equation 3.
7. Perform segmentation
8. Initialize the proposed novel approach model for training
9. Split the training and testing dataset for the novel approach model
10. Perform noval approach simulations and get accuracy.
11. Make a comparative analysis of accuracy with existing CNN models.

C. Proposed System Architecture

In the work that is being presented, once Face Recognition systems have been obtained, preprocessing is performed on face sets to provide a common dimension for the images. The Gaussian filters are used in the noise reduction stage to remove the noise. Following that, the MSE, PSNR, and SSIM are computed. To make an accurate prediction about the accuracy of a model, the novel approach Starts by setting up its classifiers, iterations, and layers. To evaluate the person behind the recommended model, a comparison of accuracy measures is performed.

Figure 1 is a representation of the system design that has been suggested. The study that is being presented is centered on Face Recognition systems that make use of a deep learning approach to evaluate face images that have been recorded. For face recognition and classification, the use of a deep learning approach necessitates the consideration of some conventional CNN

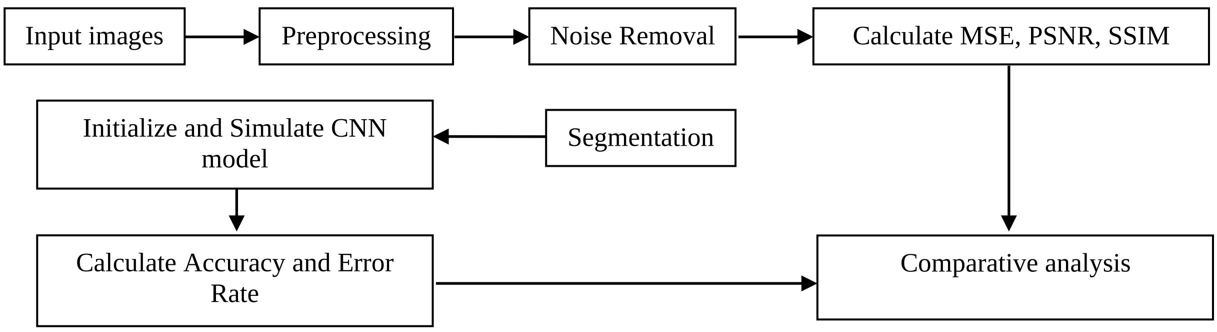

Figure 1. Proposed Innovative CNN Approach System Architecture

models. In most cases, traditional research used a CNN model that was based on either ResNet or DenseNet. A state-of-the-art hybrid model that integrates ResNet and DenseNet has been used in the technique that has been suggested. The suggested work is being promised to significantly improve both efficiency and accuracy. Both binary and categorical classes are taken into consideration during the training and testing of models in simulations. The LFW dataset supports this approach. The flow of work throughout the whole process is shown in Figure 2.

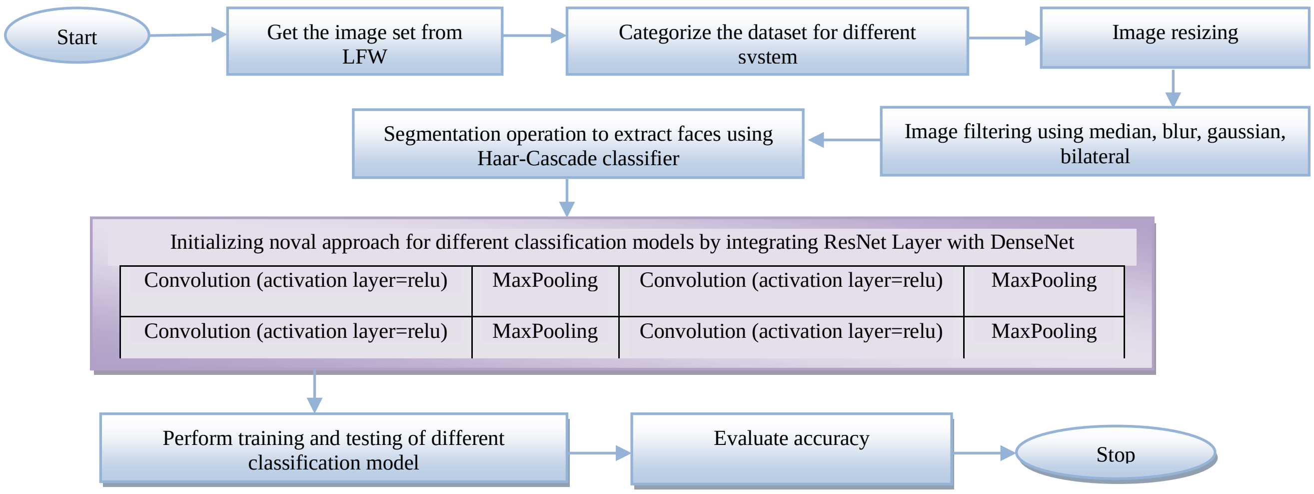

Figure 2. Flow chart of proposed work

The LFW picture collection has been considered for preprocessing, and all of these images have been compressed to get a dataset. Within the context of the system, this system plays a key role in the categorization of images. Using image filters like median, blur, Gaussian, and bilateral to reduce noise from an image is a helpful way to get a constant size for the image. Resizing also helps to do this. To do the segmentation and extract faces, the Haar cascade classifier is used. Following that, different classification models that have been constructed by merging the ResNet Layer with DenseNet are taken into consideration for training purposes so that it may examine the data. The batch size, learning rate, picture set, and epochs are all set up for training at the beginning of the process. Following that, the testing operation is carried out to guarantee the dependability of the provided model.

D. Dataset and system requirements

An extensive database of facial images called the (Labeled Faces in the Wild) LFW dataset is taken into account for the sake of the experiment. For the purpose Face Recognition system, the LFW database contains a collection of face images that have been categorized. Figure 3 presents the LFW dataset sample of images. To eliminate background noise in LFW photos, a noise filtering method was used for the captured images. With 13,233 photos from 5,749 people, the Haar-Cascade face detector is run over LFW represented in Figure 3.

Figure 3. Sample of Images from the LFW dataset [27]

E. Accuracy comparison

To predict the accuracy, the process of classification is performed [21] for the Face Recognition System. The ResNet model results were calculated during the detection of different categories to find out the True positive and true negative values correspondingly. DenseNet result has been evaluated [26] in different categories. During classification, different categories of faces are predicted in the different groups to find out the True positive and True negative values correspondingly.

Finally, the proposed novel approach is considered for the classification of different categories for the Face Recognition System. During classification, different categories of faces are predicted correctly to find out the True positive and True negative values correspondingly.

IV.EXPERIMENTAL RESULTS

This section discusses methods for eliminating noise. Following preprocessing, the picture quality is assessed by calculating the Mean Squared Error (MSE), Peak signal-to-noise ratio (PSNR), and Structural Similarity Index (SSIM). Deep learning models like ResNet, DenseNet, and Innovative CNN Approach have been used for binary and categorical classification tasks.

A. Noise removal techniques

Noise reduction was carried out using Bilateral, Blur, Median, and Gaussian filters to enhance the picture quality. The study found that the Gaussian filter produces more precise outcomes compared to the median, blur, and bilateral filters in several aspects. The simulation is first conducted for the Bilateral, Blur, Median, and Gaussian filters. Evaluation of MSE, PSNR, and SSIM values is conducted for the filters mentioned above. The Gaussian filter outperformed other filters represented in Figure 4.

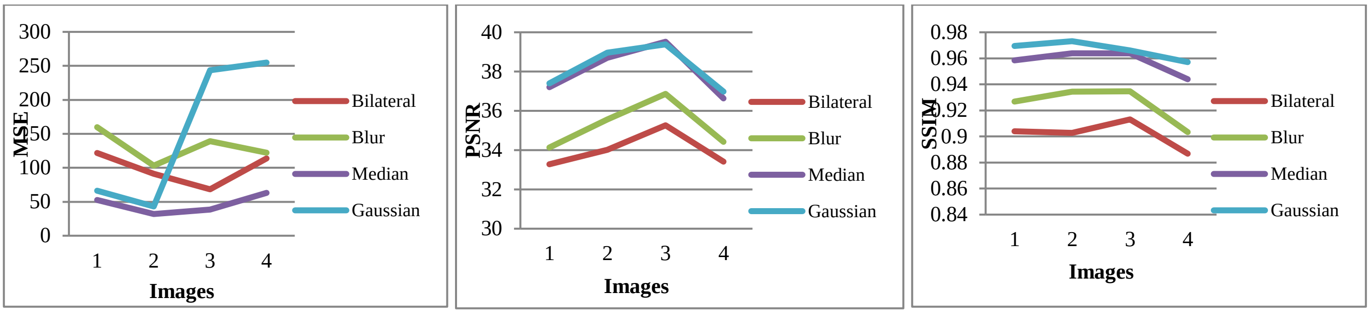

Figure 4. (a), (b), and (c) Graphical representation of Comparative analysis of MSE, PSNR, and SSIM for different filters

B. Segmentation

Then segmentation was performed on the LFW dataset was categorized, throughout the simulation to assess the accuracy of the face recognition system. The HAAR Cascade algorithm was used to segment the picture collection. Figure 5 depicts the segmented picture dataset.

Figure 5. Segmented Image set of LFW dataset

C. Performance and Accuracy

A simulation has been conducted using Google Colaboratory. Five simulations were conducted for the ResNet model, DenseNet model, and the suggested new CNN method model. Time taken for training is measured in hours for all three models. The suggested model has a shorter training time than Resnet and Densenet. The Innovative CNN approach outperformed the basic ResNet and simple Densenet models, as represented in Table I and the performance assessment graph in Figure 6.

Table 1. Performance evaluation of models

Simulation	ResNet	DenseNet	Innovative CNN Approach
1	4:04	4:10	3:51
2	4:05	4:20	3:49
3	4:10	4:30	4:00
4	4:10	4:32	3:50
5	4:20	4:40	4:20

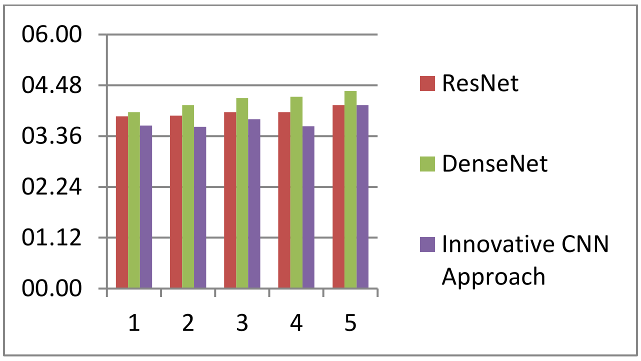

Figure 6. Performance evaluation

The model's accuracy was evaluated in binary and categorical class modes using a non-segmented picture dataset. Losses were calculated as Binary_cross entropy and Mean_squared_error, as represented in Table III and Table IV. Binary Cross-Entropy and Mean Squared Error are prevalent loss functions in machine learning, especially in neural networks and deep learning. They have distinct functions and are used for various sorts of activities. Binary Cross-Entropy, sometimes referred to as log loss or logistic loss, is mostly used for binary classification tasks involving two classes (e.g., 0 and 1). It quantifies the difference between the estimated probability distribution and the actual binary labels. The formula for binary cross-entropy is:

$$L(y,p) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \, . \, \log(p_i) + (1-y_i)\, . \log(1-p_i)] \quad (4)$$

Where y represents the true binary labels (0 or 1), p represents the predicted probabilities (usually output from a sigmoid activation function), and N is the number of samples. The method penalizes significant mistakes more severely than minor errors, thereby being influenced by the model's forecast confidence.

The model's accuracy was first evaluated in binary and categorical class modes using Nonfiltered (NGF) and Nonsegmented (NSegT) picture sets. Losses were calculated as Binary_crossentropy and Mean squared_error, then accuracy was evaluated using Gaussian filter (GF) and segmented (SegT) picture sets. Losses were calculated as Binary_crossentropy and Mean squared_error, as illustrated in Table II and graphical representation in Figure 7.

Table 2. Accuracy Measures

Approach	Loss	Class_mode	Validation Accuracy	Accuracy
NGF-NSegT	Binary_cross entropy	Binary	0.4054	0.3391
	Mean_squared_error	Categorical	0.6667	0.6667
GF-SegT	Binary_cross entropy	Binary	0.9129	0.8742
	Mean_squared_error	Categorical	0.9235	0.9326

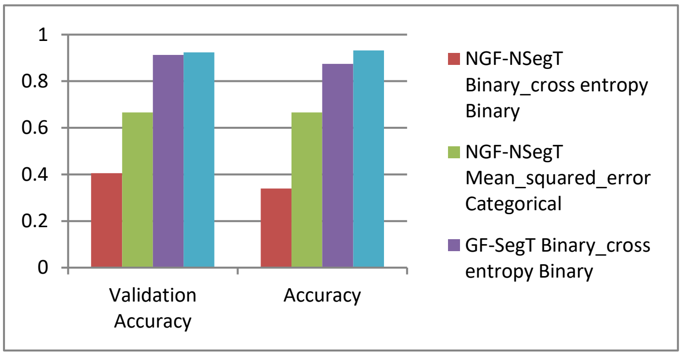

Figure 7. Accuracy measures of various approaches

D. Comparative analysis of accuracy

ResNet, DenseNet, and innovative CNN approach models are being compared based on their accuracy. Various classification models, including ResNet, DenseNet, and an Innovative CNN Approach, were introduced with 30 epochs and batch sizes of 16. An accuracy of 98% was achieved with ResNet, 97.96% with DenseNet, and 98.8% with the Innovative CNN Approach. Errors of 2%, 2.04%, and 1.2% were recorded for ResNet, DenseNet, and Innovative CNN Approach, as represented in Table III and the graphical representation in Figure 8.

Table 3. Classification of different models

Model	Epoch	Batch size	Accuracy (%)	Error Rate (%)
ResNet [25]	30	16	98	2
DenseNet [25]	30	16	97.96	2.04
Innovative CNN Approach (Proposed)	30	16	98.8	1.2

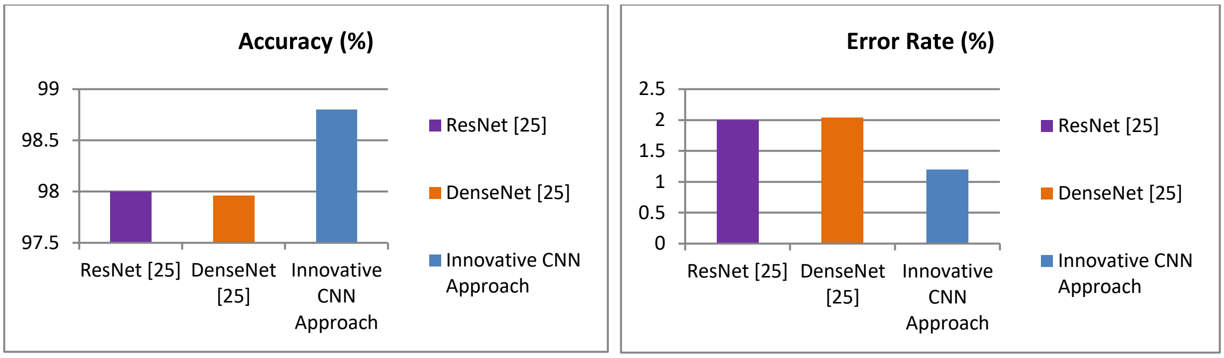

Figure 8. (a) Comparative Analysis of Accuracy **(b)** Comparative Analysis of Error Rate

V.CONCLUSION

The simulation results exhibit that the Gaussian filter produces better results in noise reduction as compared to other filters. The classification work is conducted using the publicly available benchmark LFW dataset. The novel approach system includes a noise reduction technique, a segmentation mechanism, and a ResNet model integrated into the DenseNet model based on CNN. The novel method design provides a superior degree of accuracy when compared to both existing ResNet and DenseNet models. The hybrid model ultimately achieved an accuracy of 98.8%. The simulation results show that the novel approach model outperforms the typical conventional ResNet and DenseNet models.

VI.FUTURE SCOPE

A novel approach to face recognition will be used in both governmental and commercial institutions. In the future, this model will be enhanced with sophisticated categorization techniques for the attendance system. Implementing suitable noise reduction technologies would be advantageous for future studies. In the future, models may use picture sets of high quality to verify consistency. To enhance flexibility, the model may include many face detection and recognition ideas simultaneously.

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