# End-To-End Gender Determination By Images Of An Human Eye

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**Abstract**

For immediate gender classification based on face eye images, a convolutional neural network (CNN) is presented.The suggested architecture has much less design complexity than previous CNN systems used for pattern recognition. With the use of computer vision, we can train a computer to recognize and classify things in the physical world. In this view, computer vision entails developing mathematical models that can simulate how a human's visual system and brain work. The goal is to teach computers how to recognize objects in pictures and movies. The science of computer vision and imaging makes extensive use of CNNs, a type of deep neural network. Object recognition, picture labeling, and similarity grouping are all possible with the help of convolutional neural networks (CNNs). The Sequential model will be our starting point. Last but not least, CNN is constructed using a number of layers, including an input layer, an output layer, and multiple hidden layers. Additionally, fully connected layers, convolutional, an activation function layer (typically ReLU or Softmax), normalisation layers, and pooling layers are all included in a CNN's hidden layers. This network was trained with a Sequential model, binary cross volatility as the loss function, and RMSProp as the operator. Dphi data set, which contains around 9000 pictures, is used to evaluate the suggested CNN solution. As a result of our efforts, we are able to attain a 95.78% success rate in In less than 0.27 milliseconds, a neural network can analyze and label a 32 x 32 pixel facial image, giving it the ability to scan more than 3700 images per second. A training converges within 5 epochs. These findings demonstrate that the suggested CNN is a viable method for instantaneous gender recognition.

**Keywords:** *Gender classification, Convolution neural network(CNN),RMS Propoptimizer, Sequential model, Binary crossentropy, ReLu and Softmax activation functions.*

## 1. Introduction

One of our projects involves creating a model that can tell a person's gender from an image of their eye.When it comes to craniofacial plastic and reconstructive procedures, anthropometric examination of the human face is crucial research[1]. Several variables, including age, gender, ethnicity, socioeconomic level, environment, and area, influence facial anthropometrics. The anatomical specifications of the face structures are helpful for plastic surgeons who perform procedures to correct or recreate facial abnormalities. A person's physical or facial features cause these measurements. Along with factors like culture, personality, ethnic background, age; eye appearance and symmetry contributes majorly to the facial appearance or aesthetics. Psychophysical research was the first to explore gender categorization; it seeks to comprehend human visual processing by determining the characteristics utilized to differentiate between sexes[2]. Face recognition applications in biometrics, HCI, surveillance, and computer vision may all benefit from taking use of the sex gap in facial features. Images are captured and processed, dimensionality reduction occurs, features are retrieved, and finally classification occurs as part of the standard procedure for face recognition, which includes face-based gender identification. When compared to the conventional multilayer perceptron, which consists of alternating convolutional and subsampling layers, CNNs instead include one or more completely linked layers at the conclusion (MLP). CNNs' ability to extract features, decrease data dimensionality, and categorize all at once gives them a major leg up on more traditional pattern recognition methods. By using sample data for training, the CNN is able to do feature extraction and classification simultaneously. CNNs learn from data samples to conduct feature extraction and classification within a unified network structure [4]. Furthermore, the CNN can do this without much or any preprocessing of the input picture, making it ideal for obtaining topological properties. Finally, compared to fully connected MLP neural networks with the same number of hidden layers, CNNs are more simpler to train since they contain fewer parameters. The convolutional neural network (CNN) has so far shown effective in several domains, such as character recognition [2], face identification [4], person tracking [5], traffic sign recognition [6], and many more. Around 9000 face eye images make up the dataset, which is split into training and testing datasets for model development and assessment. We suggest a convolutional neural network (CNN) with several layers, including input, output, and multiple hidden layers.Moreover, a CNN's hidden layers include a fully connected layer, convolutional layers, an activation function layer, normalization layers, and a pooling layer. There are around 20,725 eye images total, split between a training and testing set. There are 7,622 images of female eyes and 7,437 images of male eyes included in the training dataset. About 3,143 photos of female eyes and 2,523 images of male eyes make up the test dataset. We use a Sequential model, loss function based on binary cross entropy, and optimizer RMSProp to train the network.In this article, we will begin with a brief overview of the fundamentals of convolutional neural networks. After demonstrating the need for a CNN model to detect gender and age in training data, we will now design the model, show the benefits of using it, and draw a conclusion based on these results.

## 2. RELATED WORKS

Hui-Cheng Lian et al. [2] proposed a technique that employed shape and texture information from facial pictures to determine a person's gender from a picture of their face, one of many methods for doing so. Last but not least, the gender classification issue is solved using the support vector machine (SVM), which uses facial features taken from segmented images to determine the gender of the subject.Golomb et al. [4] used multi-layer perceptron (MLP) to implement a gender categorization scheme developed by Jing Wu et al. [3] based on the form shading (SFS). This was around the time when Khan et al. [5] started using classifier reinforcement, and more specifically ada boost, to make predictions about subjects' genders. Methods for analyzing craniofacial growth and images of the face and eyes have been used extensively in previous research[7,9]. In a variety of recent application domains, a deep learning convolutional neural network [11] has produced state-of-the-art results, mostly because of its greater capacity to estimate and extract features to increase the accuracy with which images may be identified.Research into pattern recognition and automated categorization is thriving, with the overarching goal of creating smart systems that can learn and recognize objects quickly and accurately[10,12,13]. Biometrics, which is often used in the context of security measures, is integral to a number of these programs' operations. The use of facial recognition technology has increased in importance as a key biometric in recent years[16,21]. The goal of this research is to use convolutional neural networks to automatically determine a person's gender and age from a still image or video of their face.The IMDB and WIKI datasets were used to test three alternative convolutional neural network (CNN) models, each of which has a different architecture (number of filters, number of convolution layers, etc.). The results demonstrated that CNN networks considerably enhance the system's functionality and recognition precision..[6,14]. Using features extracted from photographs of human faces, the authors of this research offer an automated method for making such determinations. However, the unfiltered benchmarks reveal the limitations of these conventional approaches when faced with the high levels of diversity seen in real-world facial photos. In this study, we demonstrate that deep convolutional neural networks (CNN) may be used to effectively train representations for these tasks, leading to substantial gains in performance. In this research, robust age and gender identification of unconstrained photos is achieved using an unique convolutional neural network (CNN) technique[19]. Using the Essex face dataset and the Adience standard, the ability of this study to determine gender and estimate age was evaluated. The results show how much better performance is achieved with the suggested technique, with our model attaining outstanding outcomes in age and gender classification.

## 3. METHODS USED

A. Deep Learning : The identification of central impersonation is a key application of deep learning systems. Deep learning algorithms are a part of the artificial intelligence field. Because deep learning approaches can extract high-level abstractions from data, they have recently been used to solve traditional AI challenges..[5]. Hierarchical structures, an innovative method that has been widely used in classic AI applications including semantic parsing, NLP, transfer learning, and computer vision [7], are used to facilitate this learning. Improved computer technology, decreased costs, and massive advancements in machine learning algorithms have all contributed to deep learning's meteoric development in recent years. [6].

B. Computer vision : In order to comprehend computer vision, a brief introduction to human eyesight is in need. The capacity of the human visual system to detect, identify, and interpret visual stimuli is known as vision[13]. While it doesn't take much training for a human to tell the difference between a male and female face, a computer system needs extensive instruction before it can make that determination. As an alternative definition, computer vision is the practice of training a computer to recognize and classify things in the physical world[15]. In this view, computer vision entails developing mathematical models that can simulate how a human's visual system and brain work. The goal is to teach computers how to recognize and make sense of visual content.

C. Neural Networks : Numerous deep learning methods use multi-layered feed-forward neural network designs. These layouts have each layer's neurons linked to the neurons in the next layer down. We may refer to all the layers in between the input and output layers as "hidden layers" [6]. Most artificial neural networks use mathematical representations of equations to stand in for "artificial neurons." The artificial neurons are described by these equations, which imitate the organic brain architecture. For a certain neuron, we define as an input vector, a weight vector, and a bias of b. The neuron's output will therefore

$$Y = \sigma(\omega.x + b)$$

where ,σ represents an activation function.

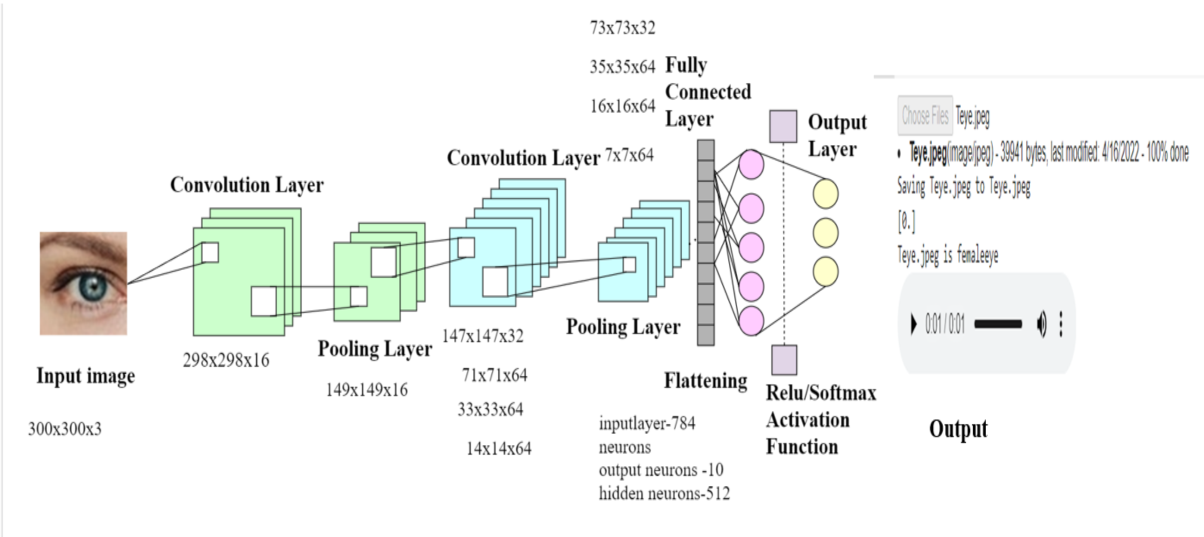
## 4. PROPOSED SYSTEM

In the fields of pattern recognition and machine learning, convolutional neural networks are among the most effective and commonly used techniques now. Convolutional neural networks, a sort of deep feed forwarding network, have been shown to have greater accuracy and speed with time, making them a popular option for testing image classification, segmentation, and object recognition. The first of two crucial components that make up a CNN is feature extraction. The network will go through a number of convolution layers and pooling procedures to retrieve the features. These feature sets are used by the classifier atop the fully connected layers to calculate the odds that an item is present in the image. The four fundamental components of a CNN are represented in figure 1 below as the convolutional layer, the pooling layer, the relu layer, and the fully-connected (FC) layer.The convolutional layer is responsible for creating a feature map from an input image by applying a sequence of filters to the image. Next, a pooling layer is used to combine similar characteristics into a smaller feature map. To reduce processing time, we just present the most crucial map features. From network to network, there is a broad array in how often the FC layer outputs are sent to the compact function map layers. Instead, FC layers flatten all of the maps at once and then evaluate the probabilities of each function occurring based on the other functions to get the most accurate categorization. Rectified Linear Units (Relu) layers are often used to introduce nonlinearity into a system since convolution can only carry out linear operations (element-wise multiplication and summation). Convolutional neural networks (CNN) are the most widely used feed-forward deep neural network type, making them a popular option in deep learning. It has recently gained traction in the field of computer vision. CNN is essential for medical image analysis and many other uses. In the early stages of a standard CNN, convolutional layers and pooling layers are the two most common kinds of layers. A CNN's layers are taught in a very secure fashion[17]. Below is an equation where the sum of the convolutions is utilized in place of their dot product. The k-th feature map can then be represented as

$$y^k = \sigma(\sum_m \omega_m^k * x_m + b_k)$$

An asterisk (*) stands in for the convolution operator and the filters whenever a collection of input feature maps is summed.

**Fig.1.Convolution neural network Architecture for Gender determination**




A. Detailed convolution neural network architecture for gender determination

We have constructed five distinct convolutional neural networks (CNNs) with varying filter sizes, pooling layers, and convolutional layers for use in our experiments (CNN 1, CNN 2, CNN 3, CNN 4, and CNN 5). In Fig. 2, many CNN architectures are displayed. Investigated and contrasted is the impact of a convolutional neural network's depth and size filters on the accuracy of gender prediction.The first convolution layer employs 16 3x3-pixel kernels for use in determining a person's gender based on an image of their eye. All all, CNN2, CNN3, and CNN4 have 32 kernels that are 3x3 pixels in size. CNN5's final layer has 64 3x3-pixel filters. A pooling layer, or flattening layer, follows each convolution layer. After the first four pooling levels, a flattening and Relu activation function layer comes next, and finally an output layer. A flattening layer, a softmax activation function, and the final convolution and pooling layers are followed by an output layer.The image is 300x300x3 pixels in size when submitted. When the input image is passed through CNN1(i.e the first convolution layer) the output shape of the image is 298x298x16.The image is then processed through a pooling layer, resulting in a 149x149x16 pixel format.Now after the second convolution the output size of the image is 147x147x32 and for the pooling layer is 73x73x32.The output size of the image after third convolution is 71x71x71 and pooling layer is 35x35x64.After the fourth convolution the output size of the image is 33x33x64 and pooling layer is 16x16x64.The outputsize of the image after final convolution and pooling operations are 14x14x64 and 7x7x64 respectively. Any convolutional layer may take an image as input, and it will generate feature maps as its output. Each feature map is convolved with a weighted filter set before non-linearities like ReLU are applied to the resulting weighted sum. While the filters used by each feature map are different, those used by the neurons that make up that map are the same.

Input image: A convolutional neural network (CNN) starts with an image as input. The subject matter of a picture is not limited to humans; it may be of any other creature, of any natural or artificial setting, or even of a medical X-ray. In this case, a picture of a human eye serves as the input image. Every image is turned into a matrix of ones and zeros. The input image is shown in fig.2.

**Fig.2.Sample of the input image**

Pooling layer: As a general, a pooling layer will be utilised in between the two convolutional layers that follow it. By downsampling the representation, the pooling layer lowers the number of parameters and the amount of processing.You may choose between a maximum and an average pooling function[13]. Since max pooling is more efficient, it is often utilized. Reduce the amount of parameters and calculations required by a network with the help of a pooling layer that flattens the spatial representation produced by a convolutional layer. Using a stride parameter analogous to a filter of a convolutional layer, pooling operates autonomously on every depth slice of its input. Maximum calculation is often used for pooling. The pooling layer allows us to overlook irrelevant features and further compress the image without losing its unique characteristics. To further decrease the picture while maintaining the most important portion of the image, a pooling layer is applied to the feature map generated by the convolution layer[19]. Maximum pooling, minimum pooling, and average pooling are all examples of operations that may be found in the pooling layer. This is achieved by first choosing a matrix size, say 2x2, and then scanning the feature map to find the largest integer that can be included inside that matrix. The following image illustrates the concept of maximum pooling.

Flattening: A convolutional neural network receives an image after it has been compressed (CNN). The final step is to compress the merged image into a single straight axis. Columns are created from each row and piled on top of one another.

**Fig.3.Detailed convolution neural network architecture for gender determination**

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d (Conv2D) | (None, 298, 298, 16) | 448 |
| max_pooling2d (MaxPooling2D) | (None, 149, 149, 16) | 0 |
| conv2d_1 (Conv2D) | (None, 147, 147, 32) | 4640 |
| max_pooling2d_1 (MaxPooling2D) | (None, 73, 73, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 71, 71, 64) | 18496 |
| max_pooling2d_2 (MaxPooling2D) | (None, 35, 35, 64) | 0 |
| conv2d_3 (Conv2D) | (None, 33, 33, 64) | 36928 |
| max_pooling2d_3 (MaxPooling2D) | (None, 16, 16, 64) | 0 |
| conv2d_4 (Conv2D) | (None, 14, 14, 64) | 36928 |
| max_pooling2d_4 (MaxPooling2D) | (None, 7, 7, 64) | 0 |
| flatten (Flatten) | (None, 3136) | 0 |
| dense (Dense) | (None, 512) | 1606144 |
| dense_1 (Dense) | (None, 1) | 513 |

Total params: 1,704,097
Trainable params: 1,704,097
Non-trainable params: 0

Fully connected layer

This layer is made up of feed forward neural networks. The completely interconnected stages are the culmination of any network. The last pooling or convolutional layer's output is "flattened" before even being delivered to the fully connected layer. A three-dimensional matrix is produced after a pooling and convolutional layer; this matrix is "flattened" by "unrolling" its values into a vectors. This decreased vector is then added to a few fully linked layers, simulating Artificial Neural Networks in terms of mathematical processes. Each ANN layer undergoes the following procedure.,

$$\boldsymbol{g}(\boldsymbol{W}\boldsymbol{x}+\boldsymbol{b})$$

Where, x — is the input vector with dimension [p_l, 1].

W — Is the weight matrix with dimensions [p_l, n_l] where, p_l is the number of neurons in the previous layer and n_l is the number of neurons in the current layer.

b — Is the bias vector with dimension [p_l, 1].

g — Is the activation function, which is usually ReLU.

After an input has been processed by all fully linked layers, the probability that the input belongs to a certain class is calculated using the ReLU activation function (classification).

B. Network structure for gender prediction

We have constructed five distinct convolutional neural networks (CNNs) with varying filter sizes, pooling layers, and convolutional layers for use in our experiments (CNN 1, CNN 2, CNN 3, CNN 4, and CNN 5). Table 1 details the many types of CNN designs. The five convolution layers and two more iterations of the same configuration used by the CNN are shown in the table below. Each of the three convolutions consists of a pooling layer, two fully linked layers, and five convolution layers. Parameters for the filters included in a convolutional layer must be learnt. The filters have a lower volume and a lighter weight than the input volume. Feature maps composed of neurons are computed by convolving each filter with the input volume. This involves translating the filter in two dimensions across the input and computing the dot product at every conceivable location where the two variables intersect. The output volume of the convolutional layer is calculated by stacking each of the feature maps from the filters along the depth axis. Since each filter aims to have dimensions lower than the input, each neuron in the activation map is only linked to a small piece of the input region. The size of the filter is comparable to that of each neuron's receptive field. The local link is supported by the cell structure in the animal visual cortex, where the receptive fields are rather tiny [9]. The geographic local correlation of the input and the local connection of the convolutional layer may be used by the network to train filters that react to a specific region more efficiently (for an input image, a pixel is more correlated to the nearby pixels than to the distant pixels). The filter parameters are also constant across all local locations since the filter and input are convolutioned to produce the activation map. To improve expression, learning, and generalization efficiency, the number of parameters may be reduced through weight sharing. The first stage of any picture filtering or processing is the convolution layer. There are two components that make up a convolution layer.

Feature detector or filter or kernel: This matrix is applied to a 2D picture in order to convert it into a feature map; in practice, it is roughly equivalent to a 3x3 matrix.

Feature map: Convolution of an image and feature detector yields this reduced image. In order to create a more compact version of the original image, we must first apply the feature detector to all of the image's available places. Through a dot product with the kernel matrix, the input image is utilised to create the derived image's feature map.

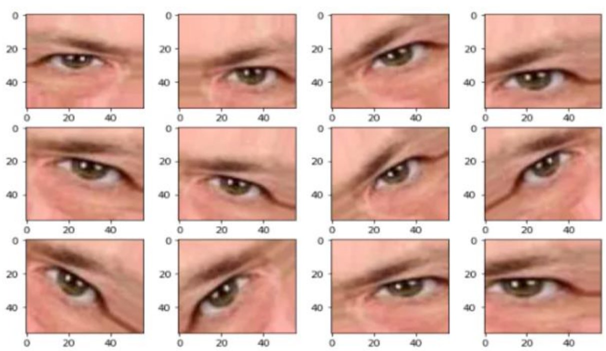
**Table.1. Convolution networks configuration models for gender determination.**

| | CNN 1 | CNN 2 | CNN 3 | CNN 4 | CNN 5 |
|---|---|---|---|---|---|
| Convolution | 16@ 3x3 | 32@ 3x3 | 32@ 3x3 | 32@ 3x3 | 64@ 3x3 |
| MaxPooling | 2x2 | 2x2 | 2x2 | 2x2 | 2x2 |
| Fullyconnected layer 1 | 512 | 512 | 512 | 512 | 512 |
| Fullyconnectd layer2 | 513 | 513 | 513 | 513 | 513 |

C. Image augmentation

Similar processes are used for augmenting either images or data. As a result of image/data augmentation, we produce large quantities of images. Then, it picks photographs at random from within each batch and performs a variety of alterations to them. Images may be transformed by data by being rotated, moved, flipped, etc. As can be seen in the example below for an image of an eye, after performing this transformation, we have far more data and a lot wider variety of photos inside the batches.

**Fig.4.Sample of image Augmentation**



D. Dataset

The Keras framework was used to create the suggested CNN models in tables 1 and 2, which has numerous benefits that make the model more efficient. We sent in a total of 2500 images, including 2000 male and female photographs and 500 test images. After each of the 1500 training epochs, the accuracy of the CNN models was evaluated. Accuracy is the proportion of instances when a predicted value was the same as the actual value. The non-linear activation function (ReLu) was utilised, the convolutional and maxpooling layers were used to process the input, RMSpro was used as the optimizer for all models, as stated in Table 1, and the sigmoid function was used to the dataset.

## 5. RESULTS AND DISCUSSION

A. Expriment and result for gender prediction

Initially the data is collected and the data is loaded and the required libraries are imported. Data visualisation is the process of representing data and information visually. By using graphical representations like charts, graphs, and maps, data visualisation tools facilitate the identification of patterns, anomalies, and trends in huge datasets. The data is separated between training and testing data sets once it has been enhanced, with the augmented image being set up for each.We define the function base model at this stage; it contains the sequential model and all of the related levels. Here fitting the baseline model is done in five epochs and a new folder is created to save the model.Now the baseline model that is the sequential model is evaluated.Now the validation dataset is evaluated. The graphs of training accuracy vs validation accuracy and training loss versus validation loss are displayed below.This is the last phase where the test data is predicted using our baseline model and that prediction is saved to predict the new images in future and then Naming the columns of the prediction labels and re-ordering the indices of the prediction and data frame is created then displaying the data frame of prediction is done and the prediction file is saved in the comma separated value(CSV) format.By using the above prediction the new unseen eye image is classified. Loading the new image save in the directory Converting the image to grayscale. Visualizing the image. Checking the shape of the image because the input image to our sequential model is 300x300. Resizing the image.Converting the image into an array. Running the prediction. Viewing the class labels,here class labels are (Male and Female). Checking the label of the unseen image.

**Table.2. Gender classification rates on dataset, Mean Accuracy**

| CNN Model | Accuracy % |
|---|---|
| First Convolution | 91.34 |
| Second Convolution | 93.79 |
| Third Convolution | 90.09 |

**Fig.5. Model accuracy and Model loss**

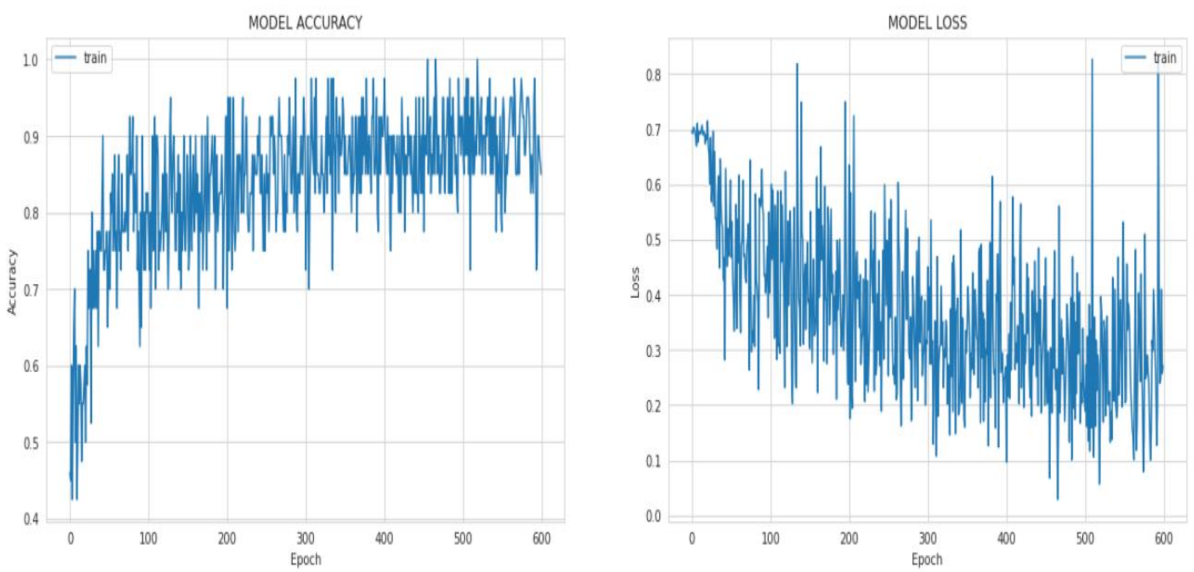
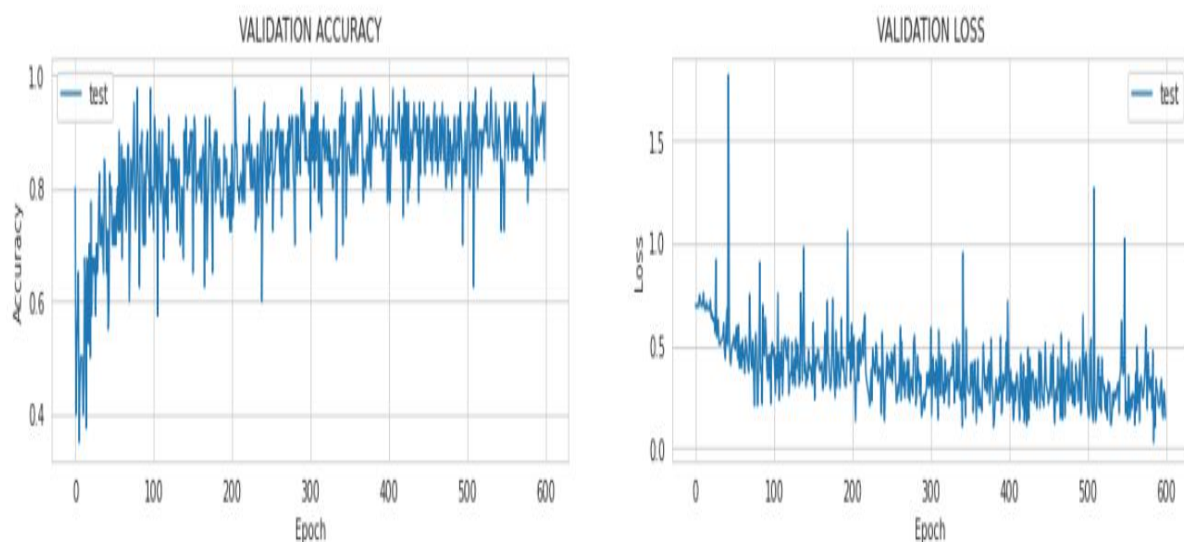



**Fig.6. Validation accuracy and validation loss**




B. Performance comparision

We showcase a comparison of the outcomes achieved by our methods and those achieved by other approaches, including the SVM classifier and the Logistic regressio. Table3 summarises the gender prediction results for several models and training datasets; our model consistently achieves the highest categorization rate.

**Table.3. Comparison of our results to the state-of-the-art in terms of gender classification efficiency.**

| Model | Dataset | Gender prediction Accuracy % |
|---|---|---|
| SVM[20] | ADIENCE | 79.3 |
| 4cef- | ADIENCE | 86.8 |

| | | |
|---|---|---|
| CNN[13] | | |
| Vgg16[21] | ADIENCE | 88.36 |
| Proposed approach | DPHI | 94.56 |

Newer methods of classifying people by their ages and sex are contrasted with our model. We find that the accuracy model for our technique is significantly better than that of previous work (table.3), with the proposed models reaching a moderate accuracy ratio (where their systems make numerous misclassifications). As we point out, the greatest results were shown on this dataset. Therefore, the proposed method not only provides the most accurate gender predictions, but it also accomplishes other aims.In addition, as the number of epochs increases, the pace at which classifications are improved demonstrates that the model acquires more knowledge as time progresses.

## 6. CONCLUSION

The ability of a deep convolutional neural network (CNN) to identify a person's gender from an image of their eye is tested and analysed in this article. The study process resulted in a plethora of potential layouts for this purpose. Research into gender classification is an important part of biometrics for social applications since it improves the reliability of predictions and the privacy of individual information. The main conclusion from this study is that gender from facial recognition is frequently utilised in social networks and advertising panels to construct a sophisticated system that may provide great and robust results in the accuracies it reaches. In order to present a clear research employing multiple CNNs model in gender categorization, we adopted a deep learning technique in the form of a convolutional neural network.Using the experimental parameters listed in table 1, we were able to analyze the data shown in Figures 5 and 6 and the results listed in Tables 2 and 3. Improved accuracy in gender categorization is a major benefit of the proposed network, but training it to make the right prediction takes a long time. The development of a face identification and recognition scheme using convolutional neural networks (CNNs) as feature extraction and the machine vector support (MVS) as a classifier, as well as testing our approach on various facial datasets with notable variations in shape and posture, could also be included in future work.

A convolutional neural network model was constructed and trained to correctly predict a person's gender based on their eye's morphometry 94.56% of the time. Gender categorization has several practical uses; for example, plastic surgeons who treat patients with facial malformations might benefit from knowing the average size of each sexe's face before beginning surgery. A person's physical or facial characteristics determine these measurements. Along with factors like culture, personality, ethnic background, age; eye appearance and symmetry contributes majorly to the facial appearance or aesthetics and also for biometrics, human– computer interactions, surveillance and in many other applications. Hence this model can be used to predict gender useful for all the above application.

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