International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-8 Issue-3, September 2019

Recognition, Classification for Normal, Contact and Cosmetic Iris Images using Deep Learning

Gino Sophia S.G., V.Ceronmani Sharmila

Abstract: ***The identification of the human being using iris based on image processing technique was one of better and older approach in human identification. Then to make human identification process an intelligent one using intelligent algorithms using machine learning techniques to train input images, extract features and classify the features based on classification techniques. The recent technology is enhancing for iris recognition based on deep learning networks, in which deeply train the images with number of layers, so that necessary features are extracted and then classify it and measure various parameters.***

Keywords: ***deep learning, intelligent algorithms, feature extraction, classification***

I. INTRODUCTION

Biometric based human identification is more difficult to hack and access the information. Iris is one of the steady and constant natural passwords among the number of biometric resources. The biometric authors used many of human related resources such as face, fingerprint, retina, DNA and iris. Many of the resources with old techniques were washed away, but different types of iris images using deep learning is now in process. The identification of human using iris is failing due to wearing of contact lenses. The occurrence of contact lenses provides problem in the case of feature identification, extraction, classification and iris segmentation. Human being are using either soft contact lenses for vision related problems or cosmetic textured contact lenses for style. eye. But colored cosmetic contact lenses are identified by colour itself. To increase the accuracy of contact lens identification requires strong field for the research society. Proposed the modal based on new existing Alexnet modal, CNN with number of hidden layers and many of feature extraction methods based on LBP, SIFT, Weighted- LBP . So that the features are refrain using CNN, Transfer learning and classification. The existing traditional system had the property of less reliability and accuracy. Also used many number of machine learning algorithms with less optimization, constrained with less features and also used linear method of classification. They used an algorithm for solving only structured data problems not for unstructured problems. The traditional conventional system solved problem using step by step instructions with suitable logic (Figure. 1). But the intelligent system means that, the system uses both image processing concepts and machine learning algorithms, like human did not used programming concept of step by step instructions but patterns are generated based on structured and unstructured input data. The natural inspired algorithms uses intelligent tools based on reliable and more accurate methodologies such as Neural Network and Fuzzy Logic. Machine learning refers to learning was performed through experience with class of event, performance measures and it will improve by experience. There are three types of machine learning techniques, such as supervised learning, unsupervised learning and reinforcement learning. In supervised method, learning was happened by an input and output. The functions of supervised learning were classification was generated categorical output and regression was produced continuous output. But in unsupervised learning method was used to discover patterns in the class. The functions of unsupervised learning method were clustering for grouping and association for frequent co-occurrences. The Reinforcement learning was based on categorical or continuous. The categorical means that of true or false problem and continuous means that about prediction of coming continuous incidents. The latest intelligent tool with upgraded features uses recent technologies such as nonlinear type of classification and solve the problem for unstructured data.

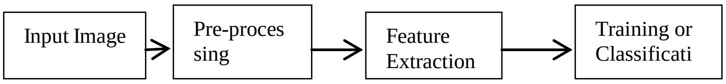


Fig.1:, Basic block diagram of traditional intelligent System

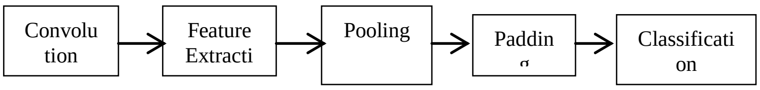


Fig. 2:, Basic block diagram of intelligent prediction system

The latest intelligent tools with many features used recent technologies such as nonlinear type of classification and solve the problem for unstructured data. The latest technology with machine learning algorithms predict about the data, analysis of data with the usage of classification models such as SVM, KNN and Naïve Bayes with increased accuracy, as a data analytics tools.

Manuscript published on 30 September 2019
* Correspondence Author
Gino Sophia S.G*., Department of Computer Science and Engineering, Hindustan Institute of Technology and Science, Padur, Chennai, Tamil Nadu, 603 103, India. Email: sgsophia@hindustanuniv.ac.in.
V.Ceronmani Sharmila, Department of Information Technology, Hindustan Institute of Technology and Science, Padur, Chennai, Tamil Nadu, 603 103, India. Email: csharmila@hindustanuniv.ac.in.

The machine learning algorithms of an intelligent system used the data as inputs, create patterns, get knowledge from the patterns, store it and predict it later. The basic diagram of intelligent prediction system is (Figure. 2).

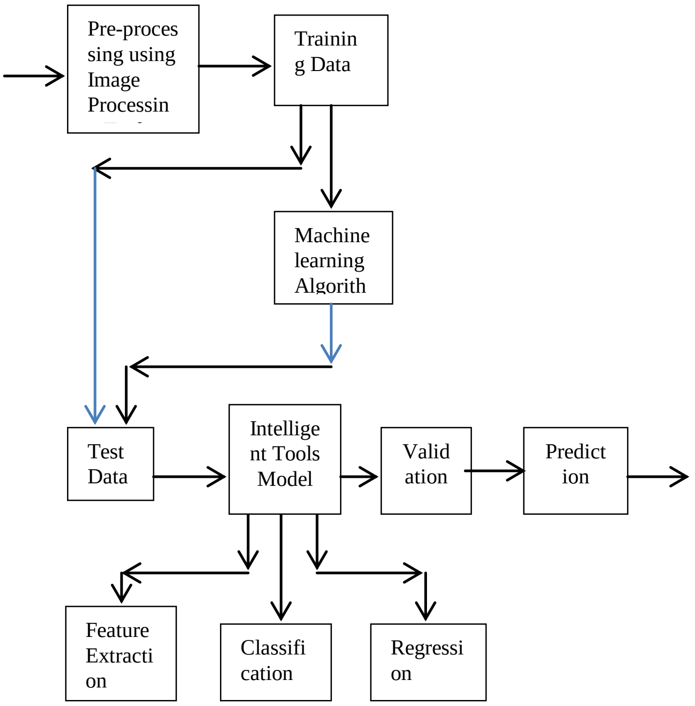


Fig. 3:, Steps of deep learning network

Deep Learning

Deep Learning is one of the types of machine learning technique in which the intelligent model makes the system as an intelligent by to do what comes naturally to humans (Figure 3). To make the system as an intelligent system by convolution neural network with a number of layers such as an input layer, number of hidden layers and an output layer, so that it can perform in the nonlinear type of data classification. The layers are unified with the number of neurons and an input of one neuron is an output of another neuron. So that each layer yields the data from the preceding layer and send to next proceeding layer so on, so that the complexity of the network increases. The researcher should know how the learning is performed and what are the features are detected for every layer by layer. During the training stage itself the neural network recognized all the features and associated similar category objects (Figure 4) and their layers (Figure 5). The basic bloack diagram of deep learning (Figure 6).

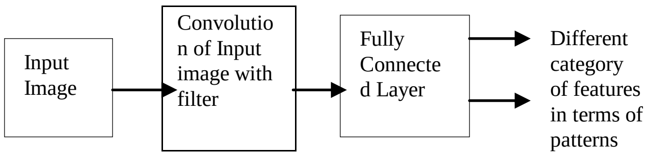


Fig. 4. Basic steps of Deep Learning

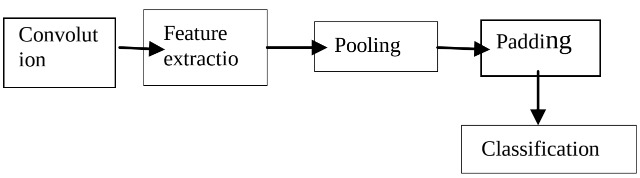


Fig. 5: Basic Layers of Deep Learning

Deep Learning Tasks

i) Easily accessed latest models such as GoogLeNet,VGG-16, VGG-19, AlexNet, ResNet-50, ResNet-101, Inception-V3.

ii) Formed, changed and investigated neural network architecture using Matlab applications and visualization tools.

iii)Categorize and classification of image data.

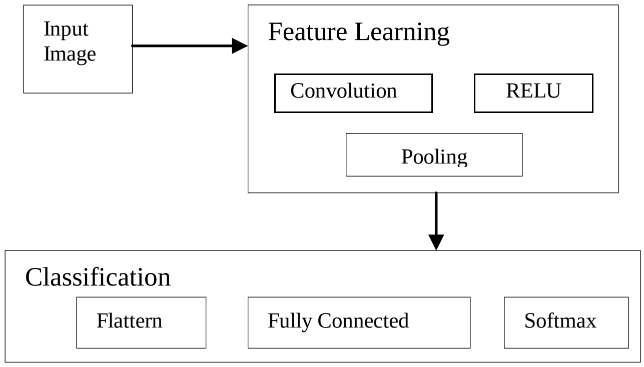


Fig. 6: Block Diagram of Deep Learning

Convolution

Convolution is one of the important features in image processing, and it is useful for feature extraction. One of the existing convolution networks was Alexnet which was trained with million numbers of images, eight deep layers and also classifies the images into number of items. Convolution takes place between an input image and a kernel filter, smaller matrix than the original image matrix. Convolution puts the input images through set of convolution filters, each of the filters motivated assured features from an image. The important task of the kernel is used for sharpening, blurring and edge detection purpose. Convolution takes place by the following steps

1. Consider an input image pixel values and kernel coefficients.
2. Multiply each kernel value with input pixel value.
3. Sum of product of kernel value and the input pixel value and the output is considered as kernel Centre.

Hrishikesh (2018) explained that Rectified Linear Unit (ReLU) was the maximum value of CNN, such that R(n) = max{0,n}, The author applied padding concepts at the time of convolution to add extra rows or columns of value of 0 to compensated the input values and kernel values. ReLU was one of fastest mapping technique to converted negative becomes zero and stored positive values. Once features were extracted using convolution, features are classified using classification algorithms. To apply deep learning techniques in between convolution and classification, learning procedures such as pooling and padding are used and necessary features for classification are finely selected. The similarity property of convolved image showed that features in one region also similar to other regions. So that calculates the mean value of specified features at a region of an image and final mean values of different regions were summarized. Pooling layer is used to reduce the dimension of an image by formation of patches with relevant information; the size of the patches may or may not be similar. The borders of the image need to be convolved using the padding concepts of extra zero pixel value.

Fully Connected Layer consists of one perceptron and it is the input for further classification of extracted features. Fully connected layer must produce outputs that can be used to measure whether the input image belongs to one of the object classes.

II REVIEW OF LITERATURE

Alaa *et al.* (2018) proposed discriminative CNN and back propagation to extract features. CNN (Convolution Neural Network) and DNN (Deep Neural Network) was applied in image processing and pattern recognition to automatically extracted features from an input image without necessity of preprocessing steps. Deep learning is the advanced of machine learning techniques that depend on high rank of demonstration and concept. CNN has a large number of features compared with DNN such as image twist, image translation, rotation and scaling. Gunjan Gautam and Susanta Mukhopadhyay (2018) suggested that iris recognition system was imitated by fake contact lens, so that author used to extract and selection of features using CNN and PCA (Principal Component Analysis). The CNN consists of number of deep layers for training data and extraction of feature based on edges and textures. Also author used PCA for feature extraction, and it consists of number of principal components and every component was grouping of number of older variables. All the principal components were orthogonal to each other and reducing redundancy of components, so that it will reduce feature vector size and computational time. Authors used Cubic SVM for classifying and training Error Correcting output code (ECOC) multiclass model for identifying occurrence of contact lens and type of a contact lens. Hrishikesh *et al.* (2018) proposed deep convolutional neural network for extraction of useful features for classification of an iris images. Author proposed optimization algorithm to extracted features in a fine tuning during training and testing stages. Also author used back propagation for selection of random values, so that it was difficult for person to attack the system. Hugo and Joao (2018) used CNN for identification and verification of an image and also CNN was used for object segmentation, detection and classification. Author considered an input image as a query during learning rate of an input image and also grouped set of similar images with label value of '1' otherwise dissimilar means label value of '0'. The selection of input images based on an iterative selective method from the collection of images using query identity, if query identity is similar so that to measure likelihood ratio of Bayes rule. Raghavendra *et al.* (2017) proposed ContlensNet using Deep CNN for detection of contact lens. ContlensNet was 15-layer model for detection and classification of different iris images. In existing technology used Gray Level Co-occurrence Matrix, LBP (Local Binary Patterns), Binarized Statistical Image Features (BSIF). Authors used subimage of size 32 x 32 and each subpart was rotated in different direction. The authors used only the iris part of size 512 x 64 of size, each image was divided into 32 parts and again every sub part was rotated 4 ways, so that totally 32 x 4 = 128 subparts were considered for next module. Pedro *et al.* (2015) used CNN for deeply illustration of input layers with weights were updated based on back propagation and fully connected softmax layer for classification. Authors used methods based on scale-invariant feature transform weighted Local Binary Patterns (LBP), Support vector machine (SVM). The existing deep learning method ContlensNet used the following specification details. Zhenan et al. (2013) proposed that the features of the iris images were classified based on SVM then apply the pooling and Hierarchical Visual Codebook (HVC) was applied for texture encoding. Hui etal. (2010) used the improved LBP (Local Binary Patterns) based on with SIFT descriptor was used for every pixel and their corresponding values were extracted. Then SVM classification was applied to every pixel for the identification of contact lens. Gino and Sharmila (2018) explained that the iris images consists of a number of unique intensity values and the dominant value is calculated based on the comparison of neighboring pixels at various directions. Also the authors have done the localization of an iris image using Zadeh max min composition fuzzy rule. Gino and Sharmila (2019) done the localization of an iris image based on morphological structuring element and the edges were detected using a canny edge detector algorithm.

1. ContlensNet used 15 layers for robust detection of contact lens.
2. The pooling applied using patches of 32 x 32 and each of patches were rotated in different angles.

III PROPOSED SYSTEM

The Matlab R2018's deep Learning Toolbox offers a framework for designing and implementing deep neural network using algorithms, pretrained models and applications, also to achieve classification and regression on images using the technique of CNN and Long Short term Memory (LSTM). The Matlab deep learning toolbox is used to create, analyze and train the networks. The deep network models such as squeezeNet, Inception-V3, ResNet-10 and GoogleNet were used for training of smaller data items. This was imported from TensorFlow Keras and caffe. It consists of number of materials such as,

i) Specification details of network architectures
ii) Numerous network configurations such as series, directed acyclic graph (DAG) and recurrent architectures were used to constructed deep learning network.
iii) Design and Analysis of neural network for deep learning.
iv) Deep learning network model is created, designed, analyzed and visualized.
v) Imported database of already trained networks for transfer learning
vi) Imported already trained networks and created model of new network.
vii) Created sufficient number of layers with own details for new layers and also for new connections.
viii) Viewed the properties of created model and edited their properties of new and existing layers.
ix) Analyzed architecture of network to confirmed their correctness by verifying through graphs and plots and identified problems for advanced training and learning.
x) Accessed pre trained models and learned features of trained models, transfer learned features to new model of layers. Pretrained models for training and learning are available

for deep learning such as squeezeNet, Inception-V3, ResNet-10 and GoogleNet.

xi) Visualization of layers, specification details, design details, analyze details were described through graphs.

xii) Plotted training process graph and learning rate of every iteration was displayed.

Matlab can be used for recognition of an iris images based on deep learning required the following toolbox for implementation of an iris images are

1. Neural Network Toolbox Model for VGG-16 network for reference models.
2. Neural Network Toolbox importer for caffe models for model importer

Neural Network Toolbox importer and pretrained network model such as AlexNet for new model importer and layer creation with new specifications.

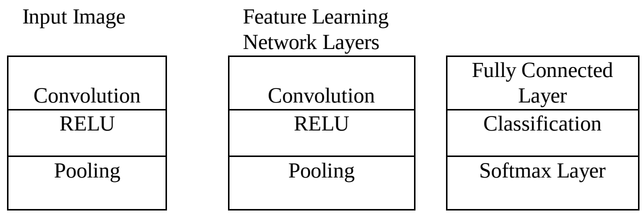


Fig. 7:, Architecture of deep learning network

The deep learning architecture consists of convolution layer, RELU layer, pooling, padding layer, Fully connected layer, Classification layer and softmax layer as (Figure 7).

Vector Convolution

Consider two vectors a = (1 1 1) and b = (1 1 0 0 0 1 1) then output z is the convolution of two vectors x and y as follows. The size (c) = size(a) + size(b) -1. Here size (c) = 3 + 7 – 1 = 9.

Step 1: c(1) = a(1) * b(1)
c(1) = 1 * 1 = 1

Step 2: c(2) = a(1) * b(2) + a(2) * b(1)
c(2) = 1 * 1 + 1 *1 = 2

Step 3: c(3) = a(1) * b(3) + a(2) * b(2) + a(3) * b(1)
c(3) = 1 * 0 + 1* 1+ 1 *1 = 2

Step 4: c(4) = a(1) * b(4) + a(2) * b(3) + a(3) * b(2) + a(4) * b(1)
c(4) = 1*0+1*0+ 1 * 1 = 1

Step 5: c(5) = a(1) * b(5) +a(2) * b(4) + a(3) * b(3) + a(4) * b(2) + a(5) * b(1)
c(5) = 1*0+1*0+1*0 = 0

Step 6: c(6) = a(1) * b(6) + a(2)*b(5) + a(3) * b(4) +a(4)*b(3)+a(5) * b(2) + a(6) * b(1)
c(6) = 1*1+1*0 = 1

Step 7: c(7) =1*1+1*1 = 2

Step 8: c(8) = 1*1+1*1= 2

Step 9: c(9) = 1*1 = 1

So that the convolution of z (1 x 9) is (1 2 2 1 0 1 2 2 1)

In general,

c(1) = a(1) * b(1)
c(2) = a(1) * b(2) +a(2)* b(1)
c(3) = a(1) *b(3) + a(2) * b(2) +a(3) *b(1)
……
c(n) = a(1) b(n) + a(2) b(n-1) + a(3) b(n-2)+…………a(n) b(1)

The output of the convolution is in equation (1).

$$O = \frac{(1 + (iw - ks + 2 * ps)}{sp} \qquad (1)$$

where iw refers to the width of the input image, ks is the size of the kernel, ps is the size of the padding and sp refers to size of the stride patch. For example, if $iw = 256$, $ks = 3, ps = 1$ and $sp = 3$, output of the convolution is 85. So that the size of an input image is 256 and it is reduced by three times with the size of an image of 85. Kernel is useful for some important task such as sharpening an image, blurring and detection of edges. For example, consider a kernel was used as sharpening purpose. Sum of multiplication each element of kernel with corresponding element of input image produced outputs and stored output in centre of an input image.

$$\text{Sharpening Kernel} = \begin{vmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{vmatrix}$$

105	102	100	97
103	99	103	101
101	98	104	102
99	101	106	104

105	102	100	97
103	89	103	101
101	98	104	102
99	101	106	104

Fig. 8:, Example of Convolution

The first move is by = 105 * 0 + 102*-1 + 100 * 0 + 103 *-1 + 99*-5 + 103 * -1 + 101 * 0 + 98 * -1 + 104 * 0 =89.
The second move is by following = 102 * 0 + 100*-1+97 *0+100*-1+103*5+101*-1+97 * 0 + 101 * -1 +102*0 = 111.

The convolved output is in the range in between 0 to 255 by number of movements (Figure 8). CNN is one of the important tools for deep learning classification and image recognition. The tasks are such as load and explore image data, define network architecture and specified training options. Trained network means that trained a Faster R-CNN (regions with convolution neural networks) was an object detector using training and learning method in deep learning, FasterRCNNObjectDetector object detected objects from an image and predicted labels of new data and calculated classification accuracy.

The existing ContlensNet used the following specification details (Figure 9), such as

1. The input image was segmented and normalized into rectangular shape image.
2. The normalized image was divided into 32 different non overlapping sub images or patches, and each of the patches was rotated in four different angles. So that the total number of patches were 32 x 4 = 128 patches.

The network architecture consists of 6 layers, once 6 layers were constructed, analysis the layers and analysis report was generated (Figure 10) and their specification details of model (Table 1).

Retrieval Number: C5185098319/2019©BEIESP
DOI:10.35940/ijrte.C5185.098319
Journal Website: www.ijrte.org

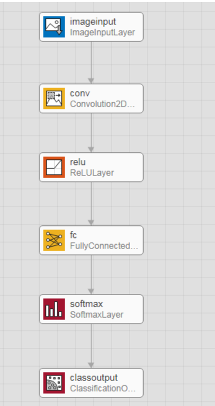
Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Table 1:, Specification details of model ContlensNet

Input rectangular shape normalized image
Convolution of 5 x 5, 256
RELU
Convolution of 5 x 5, 256
Max Pooling [2 2]
Convolution 5 x 5, 128

Layer Details
imageInputLayer([28 28 1])
convolution2dLayer(5,20)
reluLayer
maxPooling2dLayer (2,'stride',2)
FullyConnecetdLayer (10)
softmaxLayer
classificationLayer

Fig. 9:, Steps in ContlensNet



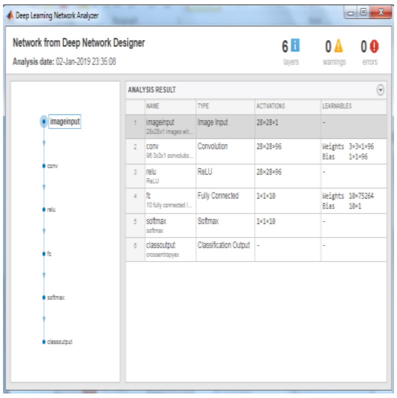


Fig. 10:, Network architecture of Deep Learning with six layers

Fig. 11:, Deep Network designers

The deep learning network was designed with 6 layers and their model (Figure 11). It consists of six layers with additional parameters such as activations and learnable. The network was analyzed that shows input image of activation was happened on multiplication of 28x96, also learning rate was based on number of parameters such as weights and bias, and learning rate based on weight was multiplied with learning rate of 3. The convolution was done for size of 28 was multiplied by 96. The relu layer forward the information and fully connected layer was learned 28x28x96=75264 of features with the learning rate of 10. The RMatlab2018b in deep learning was used for implementation of model is using following steps such as

1. Uploading database of input images
2. Divide into two parts as training and testing - Considered 60% for training and 40% for testing. So that 60% of datas were trained by neural network and 40% tested.
3. Created image input layer – The input CNN layer of 32 number of filters with 3x3 size was used. The maximum size of an image was 32.

InputLayer = imageInputLayer([32 32 3])
Define convolutional layer parameters.
Size of filters = [3 3]
Number of Filters = 32

4. Created number of middle layers – During convolution of an image is happened for smoothing of an image. Applied padding concept of adding extra rows or columns is used. Convolution layer with number of parameters such as size of filter, number of filters and padding size. The RELU layer is applied after convolution layer for further learning from pretrained models. Extended number iterations is performed for convolution,RELU, padding and pooling.
5. Created final layer based upon creation of fully connected layer with 64 output neurons. The output size of this layer is an array with a length of 64. The RELU layer is performed again after the fully connected layer. So that it can be used to measure object classes of an image. This measurement was made using subsequent layers.
6. Created softmax layer for classification after fully connected layer and it was used for prediction of images.
7. Training - Training options for stochastic gradient descent with momentum (SGDM) with number of parameters such as learning rate information, regularization factor and mini-batch size. Initial value of padding was zero. Faster R-CNN detector for detection of smaller objects from a whole image.
8. Comparison is performed between test image and trained image for calculation of training error.
9. Selected number of rectangle shape subimage from an original image for ObjectAnnotation with confirmation message (Figure 12).

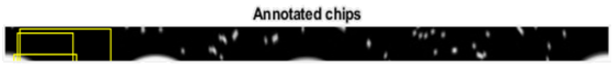


Fig. 12:, Annotation image from an original image

10. Run detector on each image in the test set and collected the results.
11. Extracted expected bounding box locations from test data.
12. Evaluated the object detector using average precision metric.

The classification layer consists of the following parameters in confusion matrix, so that, True Positive (True_Pos) is the ratio of number of precise classified images to total number of images. True Negative (True_Neg) = number of precise not classified images to total number of images.

(True_Pos)	(True_Neg)
(False_Pos)	(False_Neg)

Fig.13:, Parameter values of Confusion matrix

False Positive (False_Pos) is the ratio of number of imprecise classified images to total number of images and False Negative (False_Neg) is the ratio of number of imprecise not classified images to total number of images.The confusion matrix with four boxes with their parameter values such as True positive, True Negative, False positive and False Negative of each box (Figure 13). Calculated the parameters that were useful for validation of different types of iris images. The sparse representation was used for feature extraction and classification in class-wise deep learning. In this case training samples of each class were assumed. The confusion matrix shows that accuracy is sum of the values of True Positive and True Negative (Figure 13). Precision is the ratio of True Positive value to sum of True Positive and False Positive.

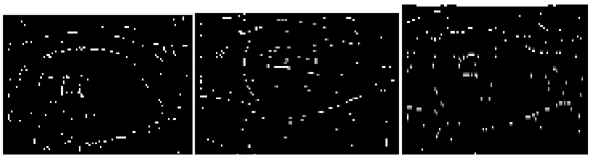
Similarly other parameter values such as Recall is the ratio of True Positive to sum of True Positive and False Negative and F-Score is the average of sum of Precision and Recall. The best value of F-Score is 1 and the worst value is 0.

IV RESULT

Consider an images of Normal, Contact and Cosmetic lens of IITD (Vista Sensor) (Figure 14) and their edges were detected using localization algorithm (Figure 15) and their localized iris images (Figure 16). Consider an images of Normal, Contact and Cosmetic lens of IITD (Cogent Sensor) (Figure 17) and their edges were detected using localization algorithm (Figure 18) and their localized iris images (Figure 19).

(a)Normal Eye Image (b) Contact Eye Image (c) Cosmetic Eye Image

Fig. 14 :, IITD Images (Vista Sensor)



(a)Normal Eye Image (b) Contact Eye Image (c) Cosmetic Eye Image

Figure 15 :, Edge Detection output (Vista Sensor)

(a)Normal Eye Image (b) Contact Eye Image (c) Cosmetic Eye Image

Fig. 16 :, Rectangular shape Iris Images (Vista Sensor)

(a)Normal Eye Image (b) Contact Eye Image (c) Cosmetic Eye Image

Fig.17 :, IITD images (Cogent Sensor)

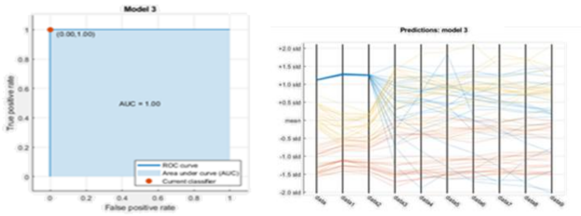
(a)Normal Eye Image (b) Contact Eye Image (c) Cosmetic Eye Image

Fig. 18 :, Edge Detection output(Cogent Sensor)

(a)Normal Eye Image (b) Contact Eye Image (c) Cosmetic Eye Image

Fig. 19 :, Rectangular shape Iris Images (Cogent Sensor)

Once the features were extracted then classified the extracted features based on classification techniques such as SVM and KNN (Figure 20 and Figure 21). The ROC and predictions graph of SVM, KNN was calculated and thir output displayed (Figure 20 and Figure 21).



(a) *(b)*

Fig. 20:, SVM classification output (a) ROC Graph (b) predictions Graph

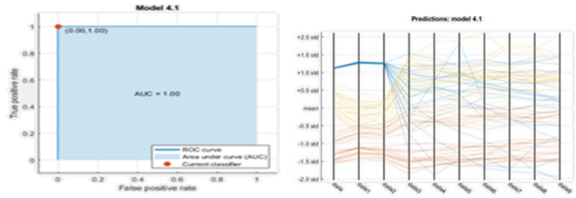


Fig. 21:, KNN classification output (a) ROC Graph (b)Predictions Graph

Table 2:, Performance Measures parameters using Deep Learning

Performance Measures	Existing Empirical Percentage by Alaa *et al.* (2018) (%)	Proposed Empirical Percentage (%)
	IITD images	
Average accuracy	95.16	95.56
Precision	92.70	93
Recall	92.68	92.82
F-score	92.69	92. 91

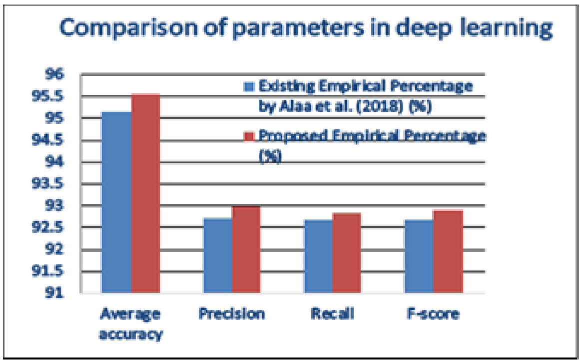


Fig. 22 :, Comparison of various parameters using deep learning

The proposed model compared existing model with number of parameters such as average accuracy, precision, recall and F-score (Table 2 and Figure 22).

.V CONCLUSION

The identification of human using iris is failed due to wearing of contact and cosmetic lenses. Now in the current situation, new techniques is necessary based on intelligent algorithms. Proposed CNN model with number of our own hidden layers and deep learning techniques. The features are refrained using CNN transfer learning and classification.

The proposed model trained the database of IITD normal, contact and cosmetic lenses images using deep learning with number of layers and generated the necessary features.
The features are classified based on classification algorithms. Then empirically measured various parameters such as accuracy, Precision, Recall and F-score. The proposed model produced empirical values such as 95.56%, 93%, 92.82% and 92.91%.

VI SUMMARY

The iris recognition system uses latest machine learning techniques based on deep learning. So here to increases empirical accuracy of detection of contact and cosmetic lenses, deep learning model is created with number of hidden layers. The hidden layers extracted the necessary features and empirical parameters are calculated. In future number of hidden Layers can be increased using Deep learning techniques and each layer can detect different features and predict using classification layers. So that different types of human diseases can be predicted efficiently based on recognition of iris images. Recognition of human identification based on coloured contact lenses is necessary in future.

REFERENCES

1. Alaa S. Al-Waisy, Rami Qahwaji, Stanley Ipson, Shumoos Al-Fahdawi, Tarek A. M. Nagem. (2018). A Multi-Biometric Iris Recognition system based on a Deep Learning approach. *Pattern Analysis and Applications. Springer.*, 21(3):783–802. *https://doi.org/10.1007/s10044-017-0656-1.*
2. Gunjan Gautam and Susanta Mukhopadhyay. (2018). Contact Lens Detection using Transfer Learning with Deep Representations. *IEEE International Joint Conference on Neural Networks (IJCNN).*, *DOI:10.1109/IJCNN.2018.8489590*.
3. Hrishikesh Menon and Anirban Mukherjee. (2018). Iris Biometrics using Deep Convolutional Networks. *IEEE International Instrumentation and Measurement Technology Conference (I2MTC).*, *DOI:10.1109/ I2MTC.2018.8409594*.
4. Hugo Proença and Joao C. Neves. (2018). A Reminiscence of Mastermind: Iris/ Periocular Biometrics by In-Set CNN Iterative Analysis. *IEEE Transactions on Information Forensics and Security.*, *DOI:10.1109/TIFS.2018.2883853*. 14(7):1702 – 1712.
5. R. Raghavendra, Kiran B. Raja and Christoph Busch. (2017). ContlensNet: Robust Iris Contact Lens Detection Using Deep Convolutional Neural Networks. *2017 IEEE Winter Conference on Applications of Computer Vision*. *IEEE Xplore.*, DOI: 10.1109 /WACV.2017.134.
6. .Pedro Silva, Eduardo Luz, Rafael Baeta, David Menotti, Helio Pedrinim and Alexandre Xavier Falcao (2015). An Approach to Iris Contact Lens Detection Based on Deep Image Representations. *SIBGRAPI Conference on Graphics, Patterns and Images, IEEE Xplore.*, *DOI:10.1109/SIBGRAPI.2015.16.*
7. Hui Zhang, Zhenan Sun and Tieniu Tan. (2010). Contact Lens Detection based on Weighted LBP. International Conference on Pattern Recognition. *DOI:10.1109/ICPR.2010.1040.*
8. S. G. Gino Sophia, · V. Ceronmani Sharmila. (2018). Zadeh max–min composition fuzzy rule for dominated pixel values in iris localization. Soft Computing, springer, *https://doi.org/10.1007/s00500-018-3651-6*,
9. S. G. Gino Sophia and V. Ceronmani Sharmila. (2019). Morphological-Based Localization of an Iris Image, Advances in Intelligent Systems and Computing, Springer. *https://doi.org/10.1007/978-981-13-1580-0_3, 2019.*
10. Zhenan Sun, Hui Zhang, Tieniu Tan, and Jianyu Wang. (2013). Iris Image Classification Based on Hierarchical Visual Codebook. , *IEEE Transactions On Pattern Analysis And Machine Intelligence.* *DOI: 10.1109/TPAMI.2013.234, 2013, IEEE.*

AUTHORS PROFILE

S.G. Gino Sophia received her Master's degree from Manonmaniam Sundarnar University, Tirunelveli and Bachelor of Engineering from Bharathiyar University, Coimbatore, Tamil Nadu, India. She has published 10 international journals and presented in 5 international conferences. Her areas of interests include image processing, soft computing and fuzzy logic.

V. Ceronmani Sharmila joined Hindustan Group of Institutions in 2003 and currently working as a Head-Centre for Networking and Cyber Defence, and HOD in the Department of Information Technology, School of Computing Sciences. She received her PhD degree from the Hindustan Institute of Technology and Science, Chennai, India in 2016. She has three years of industrial experience and 15 years of teaching experience in engineering colleges both undergraduate and postgraduate level. She has more than 30 international journal/conference publications. Her area of interest is cyber security, computer networks (mobile ad hoc and sensor networks), applications of graph theory, image processing, cloud computing, internet of things (IoT)
and very large scale integration (VLSI).