ISSN: 0974-5823 Vol. 7 No. 2 February, 2022

*International Journal of Mechanical Engineering*

# Prognostication of Diabetic Retinopathy using Transfer Learning of AlexNet

**[1]D. Umamaheswari,[2]Dr. N. Nachammai,[3]Dr. S. Anita,**

[1]Research Scholar, [2]Associate Professor

Department of Electronics and Instrumentation, Annamalai University,

[3]Associate ProfessorDepartment of Electronics and Communication,

St. Anne's College of Engineering and Technology

**Abstract**–Diabetic Retinopathy (DR) is one of the complicationswhich affects the retina and may lead to blindness in diabetes mellitus patients which can be avoided if diagnosed and detected early. Though it is often asymptotic if detected early is very much treatable. A computer vision-based algorithm can help the doctors and the patients for a faster and more precise diagnosis for treatment. Such algorithms can potentially have better accuracy in detecting different stages of the disease. However, developing such algorithms can be computationally expensive and to some extent complex in terms of extracting highly non-linear features. Applying deep learning in such scenarios increases the problem-solving capacity of the system significantly. Deep Learning algorithms have their own challenges often being dependent on corpus of labelled data. In the medical imaging field getting such large amount of labelled data can be expensive and time consuming but once completed and optimised would give a robust system for diagnosis..In this study a robust framework for the classification ofDR and healthy images were implemented. This framework using the feature map of AlexNetgives us promising results in terms of Accuracy80%.

**Index Terms – AlexNet,Deep Learning,Diabetic Retinopathy.**

## 1. INTRODUCTION

Diabetes being a chronic disease worldwide affects one out of eleven adults globally. Around 40-45% diabetes patients have a good chance of developing the diabetic retinopathy (DR) [1]. Diabetes Mellitus is a disorder which causes high chronic concentration of glucose in the blood [2]. In an estimate, more than 370 million people worldwide have a high possibility of being affected by this disease. The estimated indicate that this number can go as high as 600 million by the year 2040[1]. If this condition is not detected in the early stages, the diabetic retinopathy could potentially cause blindness [2]. The consultation of an ophthalmologist or an optometrist is required within the 3-5 years in diabetes type 1 patients after its onset.

A blood sugar control, healthy diet and lifestyles are recommended precautionary measures to avoid DR developments [3]. DR at its early stages is usually asymptomatic and often goes undetected until patients feel vision related problems such as distortions, blurs, or floaters [3]. This makes the detection of DR in its early stages highly significant for the diagnosis as well as the treatment of the patients [3].An automatic system with a deep learning algorithm for the detection of DR would help to reduce the burden on the medical professional to diagnose and on the other hand the efficiency would help them to treat more patients. The model aims to classify the DR into twoclasses in terms of Retina as shown in Fig1. There are 5 different classes onto which we could classify the DR severity. The 5 classes being: no DR, mild, moderate, severe, proliferative. To some extent this model can be made into a binary classification by fusing categories to get non-referable which is no to mild DR or (DR and no DR) versus referable which is moderate to worse DR [2].

. In order to make the diagnosis process easier to machine learning techniques used. Conventional machine learning techniques require an expert to identify the features manually. Such conventional methods depend heavily on the expert's accuracy on the feature extraction [4]. Recent developments in deep learning have been widely appreciated and applied in the domain of medical image analysis [5]. The previously complex high-level features are increasingly more understandable in advancing deep learning algorithms [5].

**Fig1a.Sample Input Images taken for Healthy patients' Experimental Results**

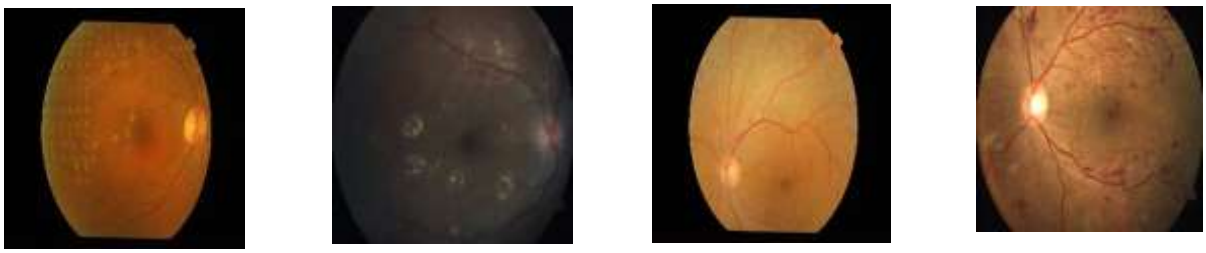

**Fig1b. Images Detected with Diabetic Retinopathy after Experimental Results**

The recent developments in deep learning have expanded the capacity of those algorithms beyond human capabilities [6]. A range of new application domains including retinal imaging analysis with not seen before specificity and sensitivity in detection and classification have been made possible with deep learning. The Convolution neural networks have proved to be a powerful tool and have been increasingly popular among researchers for DR grading [2]. Deep learning algorithms in various domains have shown to have an edge over the conventional techniques[1]. In retinal image analysis, several researchers and communities have developed algorithms to automate a computer aided analysis on retinal fundus images [1]. The detection of diabetic retinopathy is one of such conditions that can be detected with such algorithms[1].

AlexNet is one of the most powerful models in the object detection domain with high accuracies on challenging datasets. AlexNet has a huge potential in the domain of computer vision and artificial intelligence technology. The AlexNet by its architecture has been a leading model for object detection problems. The performance by AlexNet models has so appealing in recent times that it may replace the CNNs for image-based problems. The resultsfrom AlexNet could be record-breaking on highly challenging datasets.The highlight of each section of this article is summarised below.In this study we describe the development and validation of AlexNet for DR Screening, Related Works, Datasets, Proposed Architecture, Results, Conclusion and Future works

## 2. LITERATURE REVIEW

**Mohammad T. Al-Antary AND Yasmine Arafa et al** [7]. This article proposes MSA-Net or Multiscale attention network for the DR classification. The retinal image is embedded in the encoder network in a high-level representational space, the mid-level and high-level features are used to improve the representation. The retinal structure of different locality is incorporated by a multi-scale feature pyramid. A multi scale attention mechanism is used to enhancediscriminative power inrepresenting the features. The DR severity level classification done using a cross entropy loss method. The model is also trained using a weakly annotated data for healthy and non-healthy retina images. Outstanding results on experimenting this model were achieved in the public datasets of EyePACS and APTOS.

**Yehui Yang et al.[**8]The authors of this paper collaboratively used patch and image level annotations in the classification of DR severity grading. This paper presents an optimised robust framework bilaterally exchanging the information in terms of fine level lesion and image level grade. Such a framework offers to exploit more DR grading features discriminatively. The result from this article suggests outperforming the advanced modern technologies and 3 ophthalmologistspracticing over 9 years. When tested on various distribution like labelled and camera data, the algorithms prove to be resilient in real world scenarios. The CLPI in this study on extensive experiments proves to have competing performance with SOTA algorithms and other senior ophthalmologists. The paper also shows its robustness of CLPI for classification of DR grading under real world scenarios [2].

**Pengxiao Zang et al.** [9]**.** This article proposed a DR classification framework based on Conventional Neural Network (CNNs) using OCT and OCTA.DcardNet (adaptive dropout rates) is used in this framework of continuously and densely connected neural network. To address overfitting this article also proposes a adaptive label smoothing. By the guidelines of International Clinical Diabetic Retinopathy Scale three different classifications are made. On a higher level this model classifies DR asreferable (Category 1) and non-referable (Category 2). Further, on the 2ndlevel the model can classify the eye as non-DR, NPDR (non-proliferative DR), or PDR (proliferative DR). The final level classification is done as no DR, mild to moderate NPDR, severe NPDR and PDR. The adaptive label smoothing helps in network's convergence focused more on mispredicteddata. The trained model following the mentioned has better chance of handling over fitting. Such CMA generations and 3 levels of DR improves diagnosis and treatment. 95.7%, 85.0%, and 71.0 were obtained as the classification accuracy at these 3 levels respectively [4].

**Zubair Khan et al**[10]To speed up training time and convergence of model the authors have focused on classification using the lowest possible learnable parameters. A VGG-NiN model is used by stacking VGG16 as a SPP(spatial pyramid pooling layer) with NiNB(networkinnetwork)to achieve scale invariant and highly nonlinear Deep Learning model. By the virtue of SPP layerthe DR image can be processed at any scale by the VGG-NiN model. The NiN stacking helps classify better by adding a extra non linearity to the model. The results from this study suggesthaving better accuracy and resource utilisation compared to state of the art of the art technologies.

**Shuqiang Wang et al.[11]**In this article themodel uses a semi supervised multichannel-based generative adversarial network or MGAN for DR grading. A series of subfundus images with respect to the scattering DR features are generated using the multichannel generative model. The MGAN minimises the dependence of labelled data by using high-resolution fundus images without any compression. The MGAN could achieve that by identifying inconspicuous lesion features. Effective results are

obtained when the model is experimented with Messidor dataset. The model suggests to outperform in accuracy, AUC, sensitivity, and specificity.

**Mohamed M. Abdelsalam et al.[**12]In this used the Optical Coherence Tomography Angiography (OCTA) to detect diabetes. The authors explore the use of a simple Support Vector Machine method in detecting non-proliferative diabetes. Regardless, this approach was able to achieve 98.5% accuracy.**EmanAbdelmaksoud et al.**, [13] In their paper from 2021, propose the use of an effective visual feature extraction step through the use of U-Net. This is followed by producing further statistical features. These are then fed into a Support Vector Machine algorithm to achieve a very high accuracy value of 95%.**Cam-Hao Hua et al.** utilized the concept of weight sharing and reverse cross-attention to develop their convolution network. Using these two techniques, the authors were able to achieve a Quadratic Weighted Kappa rate of 90.2%. **Asra Moment Pour et al.,** in their 2020 paper, used a comparatively simpler CLAHE or Contrast Limited Adaptive Histogram Equalization method as the pre-processing step. By then leveraging the EfficientNet architecture, the authors were able to achieve an area under the curve (AUC) value of 0.936.

## 3. PROPOSED FRAMEWORK

### 3.1 Database

Kaggle data set is a huge dataset with over 15 million labelled images of highresolution in over 5000 categories. Around 100 images were used for training, 70 images for validation and 30 images were used for testing. Totally 200 images were used All the images are down sampled to about 227x227 fixed resolution to account for the variable resolution nature of Kaggle dataset. Hence the image is rescaled and then cropped out of the central 256x256 patch from the resulting image.Machine Learning Models learning simple feature with only a few thousand images were common a few years ago. The boom in data collection and accessibility of large dataset like Kaggle with hundreds of millions of images with labels has facilitated the platform to develop advanced deep learning models such as AlexNet. It is a more popular CNN used for classifier images net database.

### 3.2 AlexNetArchitecture

The innovation of the AlexNet gives significant improvement in the field of deep learning and computer vision applications. This has been proved by a large margin at the 2012 Kaggle LSVRC-2012 competition 15.3% VS 26.2% (second place) error rates. The architecture has stacked convolution layers with more filters per layer and deeper network when compared to the architecture of LeNet by Yann LeCun et al.

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Data | Conv1 | ReLU 1 | Norm1 | Pooling1 | Conv2 | ReLU 2 | Norm2 | Pooling2 | Conv3 | ReLU 3 | Conv4 | ReLU 4 | Conv5 | ReLU 5 | Pooling5 | Fc6 | ReLU 6 | Drop6 | Fc7 | ReLU 7 | Drop7 | Fc8 | Prob | Output |
| | AlexNet Convolution Layer | | | | | | | | | | | | | | | Fully Connected layers | | | | | | | | |

**Fig2.Layers in AlexNet Architecture**

The architecture of AlexNet in deep was introduced to avoid reducing size of feature maps.The 227X227X3 is the input size of image for the model.3The architectural design of AlexNet has eight layers 5 convolutions layers, 2Normalization layers, 3 max pooling layer, 3 Fully Connected layers 2Dropout layers as shown in fig.2 The model constitutes max pooling layer, 3 fully connected layers and ReLU activation function (excluding the output layer).The Parameters are chosen in such a way that the network must diagnose DR from Normal images the chosen parameters are Given in Table1.

**Table1. Parameters in AlexNet**

| S.No | Parameters | Values |
|---|---|---|
| 1. | Kernel Size | 5×5, 3×3 |
| 2. | Padding | 1 |
| 3. | Dropout | 0.5 |
| 4. | Optimizer | Stochastic Gradient descent(SGD) |
| 5. | Activation | Rectifier Linear Unit(ReLU) |

.

### 3.3 Convolution and Maxpooling Layers

The 1st convolution layer is applied on 11x11 size with 96 filters, stride 4, ReLU activation function and output feature map as 55X55X96.

**Output= (input size of the filter/ stride)+1**

The number of filters is the output feature map.This is followed by 3x3 Maxpooling layer with stride as 2 resulting the feature map as 27X27X96.In second convolution operation we have 256 filter with the filter size reduced to 5x5, stride1 ,padding2, ReLU activation functionand output size as 27X27X256. Further 3X3 max pooling layer with stride2 is applied which results in a 13X13X256 feature map.The third convolution is done with 384 3x3 filters, stride1, padding1, ReLU activation function resulting in a 13X13X384 feature map. The fourth convolution has 384 3x3 filters, stride1, padding1, ReLU activation function resulting in again 13X13X384 feature map.The final convolution layer has 256 3x3 filters, stride1, padding1, ReLU activation function resulting in 13X13X256 feature map.Hence the number of filters increases as the network goes deep implying its capacity to extract more features. Also the reducing filter size reduces the feature map size as we go deeper.Further we apply 3X3 Maxpooling a layer with stride2 resulting in 6X6X256 feature map is shown in the Ttable2.

**Table2. Fully Connected and Dropout Layers in AlexNet**

| Layers | Filters/ Neurons | Filter size | Stride | Padding | Size of feature map | Activation function |
|---|---|---|---|---|---|---|
| Input | - | - | - | - | 227×227× 3 | - |
| Conv 1 | 96 | 11×11 | 4 | - | 55×55× 96 | ReLU |
| Max pool 1 | - | 3×3 | 2 | - | 27×27× 96 | - |
| Conv 2 | 256 | 5×5 | 1 | 2 | 27×27× 256 | ReLU |
| Max pool 2 | - | 3×3 | 2 | - | 13×13× 256 | - |
| Conv 3 | 384 | 3×3 | 1 | 1 | 13×13× 384 | ReLU |
| Conv 4 | 384 | 3×3 | 1 | 1 | 13×13× 384 | ReLU |
| Conv 5 | 256 | 3×3 | 1 | 1 | 13×13× 256 | ReLU |
| Max pool 3 | - | 3×3 | 2 | - | 6×6× 256 | - |
| Dropout | Rate=0.5 | - | - | - | 6×6× 256 | - |
| Dropout 1 | Rate=0.5 | - | - | - | 6×6× 256 | - |
| Fully connected 1 | - | - | - | - | 4096 | ReLU |
| Dropout 2 | Rate=0.5 | - | - | - | 4096 | - |
| Fully connected 2 | - | - | - | - | 4096 | ReLU |
| Fully connected 3 | - | - | - | - | 1000 | ReLU |

Now dropout layers are introduced with dropout rate of 0.5. Further there is a fully connected layer, ReLU as activation function, output of size 4096 and dropout layer of0.5 fixed dropout rate and 2 fully connected layer is followed with ReLU as activation and 4096 neurons.The last layer with Softmax as the activation function we have the output fully connected layer with 2 neurons for 2 classes.Hence total learnable parameters of AlexNet architecture are 62.3 million.

## 4. EXPERIMENTAL RESULTS & DISCUSSION

The dataset used in this work is Kaggle. The input image consists of 100 retinal scans. The number of healthy patient scans is 30, and the number of diabetic patient scans is 70. This gives us a total of 100 scans, with a skew towards diabetic scans. AlexNet architecture is used in this project as it is a simple architecture, but is also able to achieve good results. The trainable parameters are 51,201.

The Performance of the Network is calculated by Confusion matrix.The confusion matrix and associated metrics presented below to get a better understanding of our model's performance.

**Table3. Confusion Matrix for the Sample Dataset**

| | True Positive | True Negative |
|---|---|---|
| Predicted Positive | 56 | 14 |
| Predicted Negative | 6 | 24 |

In the Table3. Positive label denotes a diabetic patient, and, Negative label denotes a healthy patient. Based on the confusion matrix, various metrics can be calculated as follows.

**Table4. Parametric Observations from the Predictions using AlexNet Architecture**

| Metric | Formula | Value |
|---|---|---|
| Accuracy | (TP + TN) / (P + N) | 0.8000 |
| False Discovery Rate | FP / (FP + TP) | 0.2000 |
| Precision | TP / (TP + FP) | 0.8000 |
| Recall | TP / (TP + FN) | 0.9032 |
| F1 Score | 2TP / (2TP + FP + FN) | 0.8485 |
| Specificity | TN / (FP + TN) | 0.6316 |
| False Positive Rate | FP / (FP + TN) | 0.3684 |
| False Negative Rate | FN / (FN + TP) | 0.0968 |

From the above Table4.We can see that our model's accuracy is 80.00%. Complementary to this is the False Discovery Rate of 20.00%. Together, they effectively mean that there is a 20% chance of our model could mislabel an image as the incorrect class. Our precision score tells that 80.00% of those instances we classified as diabetic were actually diabetic. The recall score tells that, of all the people who were diabetic, we correctly predicted 90.32% of them. Using the precision and recall values, the F1 Score of 84.85% we obtain is the average of the precision and recall values.

So far, the metrics we have displayed show that our model is performing well. But using more metrics allows us to get a deeper understanding of the limitations in the performance of the model. The specificity score we get has significance since it tells that of all the healthy people, we correctly labeled only 63.16% of them. Also, the False Positive Rate tells that there is a 36.84% chance that our model could label as healthy patient as having diabetes. This number is not trivial considering that the model is being used in a medical setting. Finally, our False Negative Rate tells that there is 9.68% chance that our model could label a diabetic patient as healthy.

From these helpful metrics, there are some important points to be noted. Generally, given the small training dataset size of just 100 images and also the fact we only trained it for 10 epochs our model has given good results. With a more balanced and larger dataset, paired with a better architecture, we can drastically improve our model performance. Even with ourcurrent model, we can observe that the specificity is relatively low. This is due to the small number of images we have of healthy people's retinal scans.

We can also see that our False Positive Rate is very high. Therefore, when using this model, a secondary check should be done to actually verify if the person has diabetes. Otherwise, there is good chance a healthy individual would receive treatment for diabetes. Also, the False Negative Rate is not very good. There is an almost 10% chance that our model could miss out on diabetic patients who actually need treatment. Again, we can ascertain these results to the very little number of healthy patient's scans we have

**Table5. Training cycle**

| S. No | LOSS | | ACCURACY | |
|---|---|---|---|---|
| | **Training** | **Validation** | **Training** | **Validation** |
| 1 | 3.5623 | 0.9839 | 0.7531 | 0.6000 |
| 2 | 2.9423 | 0.1695 | 0. 8914 | 0.8000 |
| 3 | 2.3673 | 0.6271 | 0.8936 | 0.8000 |
| 4 | 0.5440 | 0.3473 | 0.8700 | 0.9000 |
| 5 | 0.4390 | 0.1176 | 0.9943 | 0.9000 |
| 6 | 0.4440 | 0.4843 | 0.8125 | 0.8000 |
| 7 | 0.4811 | 0.7737 | 0.8958 | 0.8000 |
| 8 | 0.4450 | 0.1627 | 0.8035 | 0.8000 |
| | **Average** | **0.4285** | **Average** | **0.8000** |

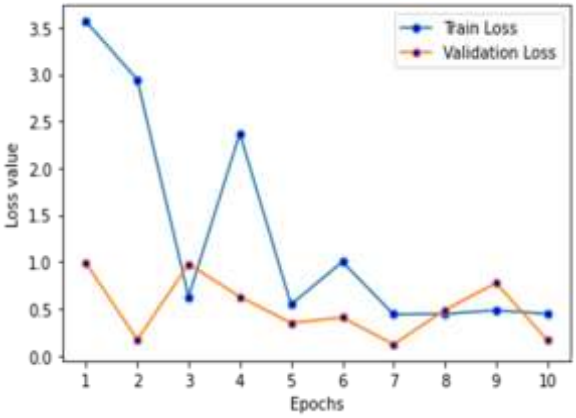


**Fig3. Training Loss Vs Validation Loss**

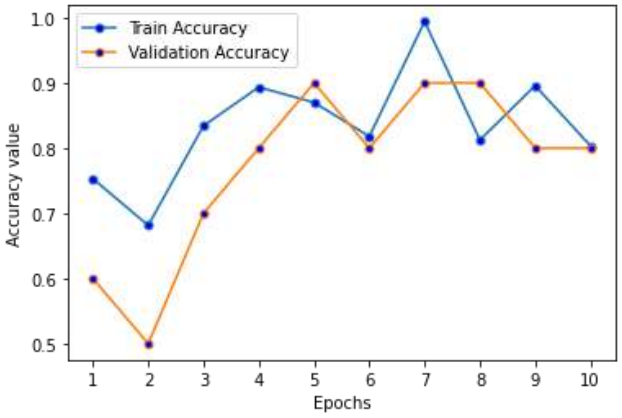


**Fig4. Training Accuracy Vs Validation Accuracy**

Fig3.Shows the convergence train and validation losses achieve as the epoch's progress as well as training and validation accuracies as the epochs progress. . We can particularly see how similar these two accuracies get in the final epoch showing very high generalization. These are confirmed by the Table5.

By taking a look at the network performance as the epochs progressed, we can make twoimportant observations. Though the neural network starts with disparate train and validation losses, it converges towards a train accuracy of 80.35% and validation accuracy of 80.00%. These values are very similar, and this informs us that the model has achieved good generalization. Secondly, we also observe that the validation loss is lesser than the train loss.

The above two observations mean that our validation set is well-chosen and that the model has not overfitted to the train set. Together, these two observations mean that our model is robust even with very little epochs. This is significant considering the previously stated skewness present in our dataset.

.

## 5. CONCLUSION

In this paper, we have developed a very simple CNN model for diabetic retinopathy classification using the AlexNet architecture. We aim to show how even such a simple model can perform well despite small dataset sizes. The dataset used is a simple set of 70 diabetic patient scans and 30 healthy patient scans. As is evident, the dataset is skewed. Regardless, the model performs well and is able to achieve a prediction accuracy of 80%.

There are three contributions to the proposed AlexNet model. 1) Use of ReLU activation to speed up training time. 2) Use of multi-GPU training to improve efficiency in training the model. 3) Use of overlapping pooling to reduce the chance of overfitting. The model is able to produce a generalizable solution within 10 epochs. The model developed shows promise, and with better quality data and improved training, it can give far superior performance.It is concluded that the proposed solution opens ground

for further research work to be conducted in the direction of using simple deep learning models to achieve good generalizable solutions.

**REFERENCES**


[1] J. J. Raval and R. Gajjar, "*Real-time Sign Language Recognition using Computer Vision*," 3*rd International Conference on Signal Processing and Communication (ICPSC)*, 2021, pp. 542-546, doi: 10.1109/ICSPC51351.2021.9451709.

[2] G. G. S, P. N, A. Yaji, A. M, A. M. Dsilva and C. S R, *"Review on Text and Speech Conversion Techniques based on Hand Gesture," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), 2021, pp. 1682-1689, doi: 10.1109/ICICCS51141.2021.9432277.*

[3] D. Gangadia, V. Chamaria, V. Doshi and J. Gandhi, *"Indian Sign Language Interpretation and Sentence Formation*," IEEE *Pune Section International Conference (PuneCon), 2020, pp. 71-76, doi: 10.1109/PuneCon50868.2020.9362383.*

[4] D. Gangadia, V. Chamaria, V. Doshi and J. Gandhi, *"Indian Sign Language Interpretation and Sentence Formation*," IEEE *Pune Section International Conference (PuneCon*), 2020, *pp. 71-76, doi: 10.1109/PuneCon50868.2020.9362383.*

[5] V. Kumar, S. Singh, R. Pal and A. Tiwari, "*Ad-Libbed Hand Motion Acknowledgment Framework Utilizing PCA," International Conference on Advances in Computing, Communication&Materials(ICACCM),2020,pp.76-81,doi: 0.1109/ICACCM50413.2020.9212940*.

[6] P. Sonawane, K. Shah, P. Patel, S. Shah and J. Shah, *"Speech To Indian Sign Language (ISL) Translation System," International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), 2021, pp. 92-96, doi: 10.1109/ICCCIS51004.2021.9397097.*

[7] Mohammad t. Al-antary and yasminearafa, "*Multi-scale Attention Network for Diabetic Retinopathy ClassificationIEEE Access VOLUME XX, 2021.DOI: 1.3070685*

[8] Yehui Yang et al"*Robust Collaborative Learning of Patch-level and Image-level Annotations for Diabetic Retinopathy Grading from Fundus Image*" *Computer Vision and Pattern Recognition. 2021 DOI: 10.1109/TCYB.2021.3062638*

[9] Pengxiao Zang, Liqin Gao, Tristan T)"*Diabetic Retinopathy Classification at Multiple Levels Based on Structural and Angiographic Optical Coherence Tomography*."*2021(DOI:10.1109/TBME.2020.3027231 )*

[10] Zubair khan1, fiaz gul khan 1, ahmad khan1**, "***Robust Collaborative Learning of Patch-level and Image-level Annotations for Diabetic Retinopathy Grading from Fundus Image"2021.( DOI 10.1109/ACCESS.2021.3074422,)*

[11] Xincheng TianXiujing Wang"*A Semi-Supervised Fault Diagnosis Method Based on Improved Bidirectional Generative Adversarial Network "2021(*Appl. Sci. 11*(20), 9401)*

[12] Mohamed M. Abdelsalamet al."*Enforcing artificial neural network in the early detection of diabetic retinopathy OCTA images analysed by multifractal geometry*"2020**.** ***(DOI: 10.1080/165836552020.1796244.***

[13] EmanAbdelmaksoud "*Diabetic retinopathy grading system based on transfer learning* "*International Journal of Advanced Computer Research,*2020 *Vol 11(52) ISSN 2249-7277 ISSN (Online): 2277-7970 http://dx.doi.org/10.19101/IJACR.1048117*

[14] M. Fora, B. Ben Atitallah, K. Lweesy and O. Kanoun, "*Hand Gesture Recognition Based on Force Myography Measurements using KNN Classifier,*" *18th International Multi-Conference on Systems, Signals & Devices (SSD), 2021,pp. 960-964, doi: 10.1109/SSD52085.2021.9429514*

[15] D. Tasmere and B. Ahmed, "*Hand Gesture Recognition for Bangla Sign Language Using Deep Convolution Neural Network,*" *2020 2nd International Conference on Sustainable Technologies for Industry 4.0 (STI)*, 2020, *pp. 1-5, doi: 10.1109/STI50764.2020.9350484*.

[16] V. Kumar, S. Singh, R. Pal and A. Tiwari, "*Ad-Libbed Hand Motion Acknowledgment Framework Utilizing PCA,*" *2020 International Conference on Advances in Computing, Communication & Materials (ICACCM), 2020, pp. 76-81, doi: 10.1109/ICACCM50413.2020.9212940.*

[17] K. Bhat and C. L. Chayalakshmi, *"Advanced Glove for Deaf and Dumb with Speech and Text Message on Android Cell Phone," IEEE International Conference for Innovation in Technology (INOCON)*, 2020, *pp. 1-7, doi: 10.1109/INOCON50539.2020.9298283*.

[18] M. Agrawal, R. Ainapure, S. Agrawal, S. Bhosale and S. Desai, *"Models for Hand Gesture Recognition using Deep Learning," IEEE 5th International Conference on Computing Communication and Automation (ICCCA), 2020, pp. 589-594, doi: 10.1109/ICCCA49541.2020.9250846.*

[19] R. R. Koli and T. I. Bagban, *"Human Action Recognition Using Deep Neural Networks," Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4)*, 2020, pp. *376-380, doi: 10.1109/WorldS450073.2020.9210345*.

[20] G. Jayadeep, N. V. Vishnupriya, V. Venugopal, S. Vishnu and M. Geetha, "*Mudra Convolutional Neural Network based Indian Sign Language Translator for Banks," 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2020, *pp. 1228-1232, doi: 10.1109/ICICCS48265.2020.9121144.*