ISSN PRINT 2319 1775 Online 2320 7876

Research paper Volume 10, Iss 8, 2021

Comparative Analysis of CNN Models for RetinalDisease detection

D.Raghunath Kumar Babu, C.Prabhavathi, P.Vijaya Kumari ,K.Chandrasekhar, S.Ghouhar Taj

Assistant Professor(Adhoc)CSE Department,JNTUACEP, raghunath.d29@gmail.com
Assistant Professor(Adhoc) CSE Department,JNTUACEP, prabhavathi1231@gmail.com
Assistant Professor(Adhoc) CSE Department,JNTUACEP, vijaya.jntuacep@gmail.com
Assistant Professor(Adhoc)CSE Department,JNTUACEP,chandra507shiva@gmail.com
Assistant Professor(Adhoc)CSE Department,JNTUACEP,sgtaj786@gmail.com

***Abstract*—**Machine learning, with all its predictive capabilities has leant its services to the field of healthcare extensively. One of the many use cases of ML in healthcare is eye disease detection. Eye diseases have been rampant in society for a long time now. Diseases like Retinoid defects, Cataract, and Glaucoma are some of themore common issues in the sector now. Because of the significant nature of the issue, it's early detection and diagnosis is extremely important. It can otherwise lead toterminal after-effects like vision loss. Transfer Learning is one more approach which has been utilized in the sectorof eye disease detection. In this paper, a comparative analysis has been carried out on a multi-image fundus dataset, which analyses and compares the performance of5 transfer learning models on account of metrics like accuracy, precision and recall score. This paper exploits the usage of models like VGG16, MobileNetV2, DenseNet121, ResNet50, EfficientNetB0, ConvNeXtXLarge, and CNNs. The selected model will contribute to the sector and lend its predictive abilities to improve detection rate for optical diseases.

Keywords*—*Retinal Disease detection, Deep learning, CNN, Transfer Learning, Image Analysis

I. INTRODUCTION

Eye diseases are a significant global health concern, affecting millions of people and causing vision impairment or blindness. According to World Health Organization, more than 253 billion people worldwide are visually impaired, and 26 million of them are absolutely blind. Of all these impairments, approximately 80% is treatable. Early detection and diagnosis of these diseases are crucial to prevent vision loss and improving patient outcomes. However, early detection of such eye diseases can be difficult, due to their asymptomatic nature, until the disease itself matures to the last stage. Traditional methods of detection can be time consuming and manually exhaustive, which is why automation of such processes is crucial to the development of the medical sciences. Diseases like Diabetic Retinopathy, Glaucoma and Retinal Cancer are imperative to future vision loss and can be fatal otherwise, if detection and diagnosis isn't done early enough. All DED types have the possibility of resulting in vision loss from age 20-74 years. Diabetic Retinopathy is the result of damage to blood vessel caused by direct sunlight or too much exposure to light. This severely affects the retina, at the back of the eye. Glaucoma damages the optic link nerve between the brain and the eye, due to high pressure of the eye fluids. Diabetic Macular Edema is caused when eye fluid is collected inside the eye and left there without treatment, usually as a result of damage to the optic nerve. [1] A genetic mutation gives rise to Retinal Cancer. Changes to the genes in a child's eye can lead to such impairments.

In recent years, there has been a significant focus on leveraging Deep Learning methods to detect various optical diseases. Numerous studies have explored the potential of these methods, and their performance is often influenced by the specific hyperparameters employed in each neural network [2]. However, addressing the challenges posed by limited resources and achieving optimal results for specific tasks can be accomplished through Transfer Learning. Transfer Learning is an approach that capitalizes on pre-trained neural networks to solve real-life problems. It involves repurposing a model originally developed for a particular task to tackle a different task. This technique has proven to be highly effective in enhancing machine performance, particularly when resources for the second task are scarce. Transfer Learning offers several advantages, including convenience, speed, and the ability to obtain optimal results for a wide range of problems. The essence of Transfer Learning lies in transferring the knowledge gained from a prior task to a new task by assigning similar weights and hyperparameters. By doing so, a solid model can be constructed based on a foundation of limited training data. This approach is particularly useful when training a deep neural network from scratch is impractical or time-consuming. Several widely utilized networks have emerged as popular choices for Transfer Learning applications. These networks include Inception, Xception, ResNet, and the VGG family. Each of these architectures has its own unique characteristics, strengths, and performance capabilities, making them suitable for different types of problems. The Inception network, for example, is known for its ability to capture complex patterns and hierarchical representations. Xception, on the other hand, excels at extracting fine-grained features and achieving high accuracy. ResNet is renowned for its impressive depth, allowing it to combat the vanishing

ISSN PRINT 2319 1775 Online 2320 7876
 Volume 10, Iss 8, 2021

gradient problem and improve network performance. The VGG family of networks, with their simple and uniform architecture, has proven effective in various image recognition tasks. The use of these established networks in Transfer Learning scenarios enables researchers and practitioners to take advantage of their pre-trained weights and learned features. This significantly reduces the need for extensive training and helps achieve optimal performance even with limited data. By leveraging the knowledge captured by these networks, researchers can focus their efforts on fine-tuning the models for specific tasks, optimizing hyperparameters, and adapting the network to new domains.

Transfer learning, with its broad spectrum of applications, has proven to be an invaluable technique in various domains. Its versatility extends to areas such as agriculture [3-6], healthcare [7], entertainment, security, and many more . These applications leverage the power of pre-trained Convolutional Neural Network (CNN) models to extract meaningful features and knowledge from one domain and apply them to another. In this paper, a comprehensive comparative study has been conducted to evaluate the performance of eight state-of-the-art CNN models: ConvNeXtXLarge, EfficientNetB7, VGG19, MobileNetV2, InceptionResNetV2, DenseNet121, Xception, and ResNet50. These models have been selected due to their wide adoption, proven effectiveness, and diverse architectural characteristics. The study focuses on assessing the performance of these models using various metrics, including accuracy, precision score, recall score, and the confusion matrix. By employing these metrics, a holistic evaluation of the models' capabilities is achieved. Accuracy provides an overall measure of correct predictions, while precision score indicates the ability to correctly classify positive instances. The recall score, on the other hand, measures the ability to identify all relevant instances. Additionally, the confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives. Through this comprehensive analysis, the goal is to determine the best-performing algorithm among the selected CNN models. The results will shed light on which model excels in extracting features and making accurate predictions on the given dataset. Such insights are crucial for decision-making processes and can guide the selection of an optimal model for future applications. Furthermore, the findings of this comparative study will contribute to the advancement of transfer learning techniques in the field of CNNs. It will provide researchers and practitioners with valuable insights into the performance variations of different models and assist them in making informed choices when applying transfer learning in their respective domains.

There are several benefits to using transfer learning for detection of eye diseases. A few of them include increased accuracy of the models from being pre-trained on copious amounts of data, reduction of costs involved in diagnosis and treatment, and increased accessibility for the ease of usage of machine learning models in general, in areas where access to eye care professionals is less.

This paper has been divided into 6 subsequent parts for reader convenience. Following this section is the literature survey of related papers. Next to that is a section describing the dataset and its preprocessing details. Following that is a section describing the technologies, software and networks used in this experiment. The next section takes us through the proceedings and results of the comparative analysis, followed by the analysis and interpretation of the results. Finally, the conclusion section and acknowledgment section has been followed by a list of the references used in this paper.

II. Literature Review

Through the last few years, several automated techniques have been utilized in the detection of eye diseases to improve diagnosis and prevent negative outcomes.

In 2020, T. Nazir et al. developed a fully automated approach to detect localized disease in the optical area, through a segmentation approach. It was based on a Fast-region based Convolution Neural Network (FRCNN), and yielded an AUC score of 0.94 [8]. In 2019, M. C. Munson et al. proposed a free smartphone application CRADLE, which detects photographic leukocoria. It was successful in detecting leukocoria from photographs in 80% of the children in the experiment, 1.3 years before formal diagnosis [9]. L. jain et al. developed an automation for diagnosing diseases like diabetic retinopathy using retinal fundus images. In this experiment, they constructed a CNN for classifying the images as healthy, or diseased [10]. In 2020, M. Aamir et al. built a multi-level deep learning model for classifying affected Glaucoma images into three further categories: Moderate, Early, and Advanced. Their model acquired an accuracy of 99.39%, SE of 97.04%, and PRC of 98.2% [11]. R. Sarki et al. proposed an automation for multi-class classification considering two real life scenarios, mild multi-class Diabetic Eye Disease, and multi-class Diabetic eye Disease, in 2020. A high accuracy 88.3% was obtained for the multi-class DED, and 85.95% for the mild multi-class DED [12]. In 2020, again, A. Akram et al. proposed a novel deep learning approach for detection of eye diseases, using Deep learning architectures (CNN), and Support Vector Machines (SVM). The team performed PCA, and t-Stochastic algorithm, on the dataset for better feature selection before passing it for classification. It obtained excellent accuracy of 98.79%, specificity of 99% and sensitivity of 97% [13]. In 2018, F. Grassman et al. developed an algorithm for AMD classification of colorized fundus images. Cross validation was performed based on the sample study [14]. Again, in 2022, R. Pahuja et al. explored the use of CNN, and SVM for detection of cataract in eye images. Extensive preprocessing was done on the dataset , including data augmentation and feature etxtraction, before passing it to the proposed models. The SVM model obtained an accuracy of 87.5% and the CNN model had an accuracy of 85.4% [15]. I. Topaloglu et al. implemented a convolutional neural network based approach for detecting Diabetic Retinopathy. The model was aggregated with a care model approach, and obtained an accuracy of 88%, precision of 93% and recall of 83% [16]. K. Prasad et al. proposed a deep neural network approach to detect presence of diabetic retinopathy, and glaucoma, in their earlier stages. It can be used to warn patients from a screening point of view. This model achieved a high accuracy of 80% and had a relatively less complicated architecture [17]. Q. Abbas et al. developed a multilayer unsupervised network to extract features from raw intensity pixels. A deep

ISSN PRINT 2319 1775 Online 2320 7876
 Volume 10, Iss 8, 2021

belief network was used at the end of the architecture to extract the most discriminative features from the dataset. A softmax linear classifier provides the decisive prediction at the very end of the process. This developed model was named 'Glaucoma-Deep' and was tested on 1200 retinal images taken from both public and privately available datasets, to achieve an accuracy of 99%, a precision of 84%, and a specificity of 98.01% [18]. P. Chakraborty et al. devised a deep CNN based detection approach for identification of Pneumonia and eye diseases. The team utilized an Optical Coherence Topography (OCT) image dataset as input, and obtained a validation accuracy of 90%. The proposed model, in this case, was aimed at helping medical professionals increase their diagnostic accuracy [19].

Most of the approaches used in eye disease detection, have been deep-learning based so far, with select few exploring the performance of classical machine learning models on datasets. With optimum accuracies and high precision scores, it is easy to see why neural networks have been preferred for the job.

III. DATASET

This section has been further divided into two parts: a) Dataset Details and b) Dataset Preprocessing for reader convenience.

A. Dataset Details

The dataset used in this experiment is a collection of 3200 Retinal Fundus Multi-disease images. These images were captured using 3 fundus cameras, with 46 different parameters. This RMiFD dataset is one of the only publicly available datasets that comprise a wide variety of diseases appearing in clinical routine settings [20].

The retinal images are classified into 45 different categories. The dataset itself has 3 divisions. 60% of the datapoints constitute the training dataset, 20% datapoints are for evaluation , and the remaining 20% are for the testing dataset. The count of datapoints in each division is shown in table 1. The images were devoid of any prior preprocessing.

TABLE I. COUNT OF SAMPLES IN EACH DATASET

DataSet type	Count of samples
Training	1920
Evaluation	640
Testing	640

The labels for the dataset were provided I three different csv files. The 45 diseases present in the image dataset include Diabetic Retinopathy, Retinitis, retinal Tract Infection, Exudation, Coloboma, Vasculitis, Plaque, Collateral, Cystoid Macular Edema etc.

B. Dataset Preprocessing

Gaussian blur was applied to the dataset for denoising and removing specks in the images. It is imperative to remove the high frequency components so as to prevent detection of false detection of edges. The dataset was also passed through the NLM Denoising algorithm, to preserve the original textures of the images. Data cleaning, though a vital preprocessing step, can also mellow the predictive capability of the model, by taking away the chance to make observations on real-life data. That is why, data augmentation, which is a process of generating new, synthetic data points, with variations from the original datapoint, was also applied to the image dataset. Random rotation and rescaling were performed, so as to increase the accuracy of the model.

IV. TECHONOLOGIES / SOFTWARE USED

A. Technological Concepts Used

A total of 8 models were tested and compared in this experiment. 2 of them were customised CNN models with tuned hyperparameters, a ConvNeXtXLarge model, one EfficientNetB0 model, one VGG16 model, one MobileNetV2 model, one DenseNet121 model, and one ResNet50 model. These models are called transfer learning models, due to their ability to assign similar weights to new models, for training in image classification tasks. The weights of these models can also be fine-tuned in order to optimize them even further, resulting in improved performance. This makes these models efficient for the newly assigned tasks [21, 22]. These models and their descriptions, along with their advantages and disadvantages have been described below in table 2, followed by a brief discussion of CNN. These models offers great leverage in increasing accuracy, precision and recall of the used models. Their prior training help in recognition of pattern and identifying them.

TABLE II. RECORD OF TRANSFER LEARNING MODELS COMPARED

Model Name	Description	Advantages	Drawbacks
ConvNeXtXLarge	A pure convolutional model which claims to outperform its very own inspiration, the design of vision transformers.	Do not require human supervision for identification of important features.	Deep ConvNeXt layers are significantly slower due to operations like maxpooling, as the number of layers increases.
EfficientNetB0	A CNN architecture / scaling method which provides uniform scaling of dimensions of depth / width / height / resolution with the help of a compound coefficient	Achieve both higher accuracy, and better precision than existing CNNs, due to reduction of parameter size.	Perform poorly on hardware accelerators, due to comparably more data movement. And less computing.
VGG16	A deep CNN architecture that primarily focuses on classifying images. This particular model has 16 layers, out of which 13 are convolutional layers, 5 are pooling layers, 3 dense layers, and	This model boasts faster training speed, higher accuracy, and lesser training samples, per unit time.	It is a bulkier model, and its density of layers can lead to the vanishing gradient problem, and longer inference, and training time.

ISSN PRINT 2319 1775 Online 2320 7876
 Volume 10, Iss 8, 2021

	approximately 138 trainable parameters.		
MobileNetV2	A CNN architecture that performs well on mobile devices, and comprises an inverted residual structure, in which the residual connections are nestled between bottleneck layers.	This architecture consistently outperforms its predecessor, MobilenetV1, in terms of speed, and accuracy. It also boasts smaller computational complexity with relatively fewer parameters.	This architecture is 53 layers deep, and the resulting networks are extremely complex and are difficult to understand.
DenseNet121	A CNN where every layer is connected to every single deeper layer present in the CNN. Each layer, except for the first one, receives the output of its previous layer as input, and produces a corresponding feature map.	This architecture eliminates the vanishing gradient problem, facilitates feature propagation, and reusing of features. It also encourages reduction of parameters.	Each feature map is associated with features of the previous layers, and can hence replicate its output multiple times, causing redundancy.
ResNet50	A 50 layer CNN, which incorporates residual networks, built by stacking residual blocks on top of each other.	The multiple residual blocks enable faster training of layers.	For networks as deep as this one, detecting training errors becomes difficult.

These models have been trained on ImageNet. They have learnt the technique of recognition of a wider variety of visual patterns, and have developed corresponding feature depictions as well. The weights of these pre-trained transfer learning models have often been used as starting points, for assignment, during training of newer models.

B. *Convolutional Neural Networks (CNN)*

CNN, or Convolutional Neural Networks are classes of deep neural networks built primarily for image processing and classification/recognition. These networks comprise of four types of layers, Convolutional, Padding, Pooling, and Fully Connected. These layers supply input sequentially to each other using the output of the previous layers, as input for processing.

The basic work flow involves passing an input image, which is converted to a matrix of pixels, to the CNN through the convolutional layers. The convolutional layers work to produce an output feature map, using the convolution operation, as shown in eq. 1, and strides [23].

$$p * q[m] = \sum p[m-j]q[j] \qquad (1)$$

This feature map is then passed through the padding and pooling layers to reduce spatial dimensions, and is finally passed through the fully connected ANN, to produce a probability of the image belonging to a particular category. The two CNNs used in this experiment, were varied according to their number of convolutional, pooling, and dropout layers. The classification block at the end of each CNN is the same, and acts as the fully connected layer for both the neural networks. Architectural specifications for each CNN is shown below in table 3.

TABLE III. ARCHITECTURAL SPECIFICATIONS OF CUSTOM CNNS

S.I	Convo layers	Pooling Layers	Pooling Used	Padding layers	Padding Used	Activation Function (Conv)	DropOut layers	Kernel Size	Dense Layers
1.	4	3	MaxPooling	3	same	ReLU	3	3 X 3	3
2.	1	1	MaxPooling	1	valid	ReLU	0	3 X 3	5

The classification block added to the end of each model, consisted of one flatten layer, which flattened the output of the previous matrix. This was outputted after processing by convolutional, pooling, padding, and dropout layers, two dense layers, with 128 and 64 neurons each, and a final output layer, with the sigmoid function as activation. The mathematical definition of sigmoid function, and ReLU function is given below in equations 2, and 3 respectively.

$$F(a) = \frac{1}{1+e^{-a}} \qquad (2)$$

$$F(a) = \max(0, a) \qquad (3)$$

C. *Workstation*

The experiment was carried out on a Lenovo IdeaPad 5, on the Jupyter Notebook editor for implementation. The processor utilized was AMD Ryzen 75000 series.

V. RESULTS AND ANALYSIS

Each of the models in the experiment was trained for 10 epochs, and were subjected to k-fold means cross validation, with 'k' as 10. The performance of the various models were evaluated on the basis of three metrics, binary accuracy(BA), precision(PRC), cross-validation accuracy(CVA), and training AUC score(TAUC). The 2 CNN models were defined with 4 layers each. These values are calculated from a confusion matrix following the equations 4, and 5 respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

The AUC score of a model represents its predictive efficiency. It ranges from 0 to 1, with completely inefficient models garnering a score of 0.0, and a completely efficient one obtaining a score of 1.0. After hyperparameter tuning, The two CNN networks were defined with The metric values obtained from each of the tested models and their comparison has been illustrated in table 4, given below.

TABLE IV. METRICS OBTAINED FOR THE MODELS USED

Model	BA	PRC	CVA	TAUC
ConvNeXtXLarge	0.9384	0.2148	0.9241	0.5370
EfficientNetB0	0.9187	0.1544	0.9274	0.4992
VGG16	0.9383	0.2101	0.9414	0.5272
MobileNetV2	0.9499	0.2877	0.9512	0.5954
DenseNet121	0.9497	0.2888	0.9439	0.6061
ResNet50	0.9212	0.1615	0.9083	0.5053
CNN 1	0.9189	0.1578	0.9311	0.5007
CNN 2	0.9229	0.1593	0.5001	0.9088

From the above table, it is clearly visible that the MobileNetV2 network provided us with optimum combinations of all five metrics. With a high accuracy of 94.99%, the model was able to correctly identify and detect diseases in more than 90% of fundus images in the dataset. The training, and testing accuracy, and training and testing loss for the MobileNetV2 model, is shown below, in fig 1 and fig 2, respectively. Following the results of MobileNetV2, we saw commendable results achieved by the DenseNet121 model. This model achieved an accuracy of 94.97%, with a precision of 28.88%. Its cross validation accuracy stood at 94.39%, meaning it correctly identified more than 94% of the images, after being cross verified. The AUC score for the model 0.6061.

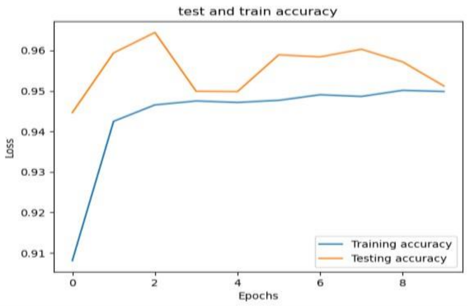

Fig. 1. Train and Test Accuracy for MobileNetV2

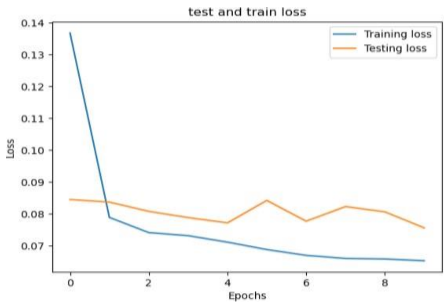

Fig. 2. Train and Test loss for MobileNetV2

VI. CONCLUSION

From the experiment, we concluded that the MobileNetV2 model, worked best for the detection and identification of multiple diseases from a fundus-image dataset. This architecture is a lightweight model was specifically designed for mobiles, and achieves higher accuracy with fewer parameters, making it an ideal choice for applications such as the one in this experiment. In comparison to the other models, MobileNetV2 also showed faster inference time, which is crucial for real-time applications.

The results suggest that the selected architecture is a promising model for image classification tasks, especially for applications where there are constraints on resources.

Overall, this study contributes to the growing body of research on image classification models and provides valuable insights into the performance of multiple models. Further research can be conducted to explore the potential of other lightweight models and their performance in various fields.

ACKNOWLEDGMENT

The first author would like to extend their sincere gratitude to all co-authors, especially, Prof. M. K. Gourisaria, for his guidance, support and cooperation.

REFERENCES

[1] R. Sarki, K. Ahmed, H. Wang and Y. Zhang, "Automatic Detection of Diabetic Eye Disease Through Deep Learning Using Fundus Images: A Survey," in *IEEE Access*, vol. 8, pp. 151133-151149, 2020, doi: 10.1109/ACCESS.2020.3015258.

[2] P. Muthukannan, 2022. Optimized convolution neural network based multiple eye disease detection. *Computers in Biology and Medicine*, *146*, p.105648.

[3] S. S. Rautaray, M. Pandey, M.K. Gourisaria, R. Sharma, and S. Das, 2020. Paddy crop disease prediction—a transfer learning technique. *International Journal of Recent Technology and Engineering*, *8*(6), pp.1490-1495

[4] S. Das, R. Sharma, M.K. Gourisaria, S.S. Rautaray, and M. Pandey, 2020. A model for probabilistic prediction of paddy crop disease using convolutional neural network. In *Intelligent and Cloud Computing: Proceedings of ICICC 2019, Volume 1* (pp. 125-134). Singapore: Springer Singapore.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper **Volume 10, Iss 8, 2021**

[5] R. Agrawal, V. Singh, M.K. Gourisaria, A. Sharma, and H. Das, 2022, April. Comparative Analysis of CNN Architectures for Maize Crop Disease. In *2022 10th International Conference on Emerging Trends in Engineering and Technology-Signal and Information Processing (ICETET-SIP-22)* (pp. 1-7). IEEE.

[6] R. Sharma, S. Das, M.K. Gourisaria, S.S Rautaray, and M. Pandey, 2020. A model for prediction of paddy crop disease using CNN. In *Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2019* (pp. 533-543). Singapore: Springer Singapore.

[7] H. G. M., A. Sahu, M. K. Gourisaria, P. K. Singh, W.C. Hong, V. Singh and B. K. Balabantaray, 2022. On the dynamics and feasibility of transferred inference for diagnosis of invasive ductal carcinoma: A perspective. *IEEE Access*, *10*, pp.30870-30889.

[8] T. Nazir, A. Irtaza, A. Javed, H. Malik, D. Hussain and R. A, Naqvi, 2020. Retinal image analysis for diabetes-based eye disease detection using deep learning. *Applied Sciences*, *10*(18), p.6185.

[9] M. C. Munson, D. L. Plewman, K. M. Baumer, R. Henning, C. T. Zahler, A. T. Kietzman, A. A. Beard, S. Mukai, L. Diller, G. Hamerly and B. F. Shaw, 2019. Autonomous early detection of eye disease in childhood photographs. *Science advances*, *5*(10), p.eaax6363.

[10] L. Jain, H. V. S. Murthy, C. Patel and D. Bansal, "Retinal Eye Disease Detection Using Deep Learning," 2018 Fourteenth International Conference on Information Processing (ICINPRO), Bangalore, India, 2018, pp. 1-6, doi: 10.1109/ICINPRO43533.2018.9096838

[11] M. Aamir, M. Irfan, T. Ali, G. Ali, A. Shaf, A. Al-Beshri, T. Alasbali and M. H. Mahnashi, 2020. An adoptive threshold-based multi-level deep convolutional neural network for glaucoma eye disease detection and classification. *Diagnostics*, *10*(8), p.602.

[12] R. Sarki., K. Ahmed, H. Wang, and Y. Zhang, 2020. Automated detection of mild and multi-class diabetic eye diseases using deep learning. *Health Information Science and Systems*, *8*(1), p.32.

[13] A. Akram. and R. Debnath, 2020. An automated eye disease recognition system from visual content of facial images using machine learning techniques. *Turkish Journal of Electrical Engineering and Computer Sciences*, *28*(2), pp.917-932..

[14] F. Grassmann, J. Mengelkamp, C. Brandl, S. Harsch, M. E. Zimmermann, B. Linkohr, A. Peters, I. M. Heid, C. Palm and B. H. Weber, 2018. A deep learning algorithm for prediction of age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. *Ophthalmology*, *125*(9), pp.1410-1420.

[15] R. Pahuja, U. Sisodia, A. Tiwari, S. Sharma and P. Nagrath, 2022. A Dynamic Approach of Eye Disease Classification Using Deep Learning and Machine Learning Model. In *Proceedings of Data Analytics and Management: ICDAM 2021, Volume 1* (pp. 719-736). Springer Singapore.

[16] I. Topaloglu, 2022. Deep Learning Based Convolutional Neural Network Structured New Image Classification Approach for Eye Disease Identification. *Scientia Iranica*.

[17] K. Prasad, P. S. Sajith, M. Neema, L. Madhu and P. N. Priya, 2019, October. Multiple eye disease detection using Deep Neural Network. In *TENCON 2019-2019 IEEE Region 10 Conference (TENCON)* (pp. 2148-2153). IEEE.

[18] Q. Abbas, 2017. Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning. *International Journal of Advanced Computer Science and Applications*, *8*(6).

[19] P. Chakraborty, and C. Tharini, 2020. Pneumonia and eye disease detection using convolutional neural networks. *Engineering, Technology & Applied Science Research*, *10*(3), pp.5769-5774.

[20] S. Pachade, P. Porwal, D. Thulkar, M. Kokare, G. Deshmukh, V. Sahasrabuddhe, L. Giancardo, G. Quellec, and F. Mériaudeau, 2021. Retinal fundus multi-disease image dataset (rfmid): A dataset for multi-disease detection research. *Data*, *6*(2), p.14.

[21] M. K. Gourisaria, R. Agrawal, V. Singh, M. Sahni and L. Raja, 2022. Comparison of Garbage Classification Frameworks Using Transfer Learning and CNN. *International Journal of Social Ecology and Sustainable Development (IJSESD)*, *13*(9), pp.1-23.

[22] V. Singh, M.K. Gourisaria, H. G.M., and V. Singh, 2021. Mycobacterium tuberculosis detection using CNN ranking approach. In *Advanced Computational Paradigms and Hybrid Intelligent Computing: Proceedings of ICACCP 2021* (pp. 583-596). Singapore: Springer Singapore..

[23] S. Sarah, V. Singh, M. K. Gourisaria, and P. K. Singh, 2021, October. Retinal Disease Detection using CNN through Optical Coherence Tomography Images. In *2021 5th International Conference on Information Systems and Computer Networks (ISCON)* (pp. 1-7). IEEE.