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AI based Diabetic Retinopathy Detection and Comparison of Different Algorithms

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Abstract— This research paper focuses on the detection of diabetic retinopathy, which a concerned medical condition. The study implemented various algorithms for diabetic retinopathy detection and compared their parameters to determine the most effective method for identifying the disease. The algorithms used in this study included machine learning-based approaches like (CNNs), (SVMs), and decision trees.Additionally, image processing techniques were utilized to preprocess the images before feeding them into the algorithms. The parameters of each algorithm were adjusted to optimize their performance on a dataset of retinal images. The results show that the CNN algorithm with specific hyperparameters outperformed the other algorithms in terms of accuracy, sensitivity, and specificity.

Keywords: diabetic retinopathy, detection, algorithms, image processing, hyperparameters, accuracy, sensitivity, specificity.

I. INTRODUCTION

Artificial intelligence (AI) and deep learning are rapidly transforming various industries, and healthcare is no exception. With advancements in computing power and data analytics, AI and deep learning are enabling healthcare providers to analyselarge dataset and timely diagnoses, as well as to develop new treatments and therapies. It is impact of AI and deep learning on the healthcare sector, examining their applications in areas such as medical imaging, drug discovery, personalized medicine, and patient care.[1] Through a review of recent studies and examples of successful implementations, thebenefits and challenges of integrating AI and deep learning into healthcare, including ethical and regulatory considerations.

One of the key advantages of AI and deep learning in diagnosis is improved accuracy. AI can identify patterns that is not visible to human physicians.[2] This can lead to more accurate diagnoses and better treatment decisions. Deep learning algorithms are trained for detection of early signs of cancer in medical images, allowing for early interventions and improved outcomes. Another advantage of AIand deep learning in diagnosis is faster diagnosis. AI and deep learning algorithms can process data much faster than humans, allowing for quicker diagnoses and treatment decisions. This can be critical in emergency situations where timely diagnosis and treatment can be the difference between life and death.

In addition, AI and deep learning algorithms offer increased objectivity in diagnosis. They can eliminate subjective biases that may affect human diagnoses, leading to more objective and consistent diagnoses. This can be particularly important in cases where diagnoses may be difficult to make, such as in rare diseases. Furthermore, AI and deep learning algorithms can provide personalized medicine. They can analyze individual patient data and provide personalized treatment recommendations, tailored to the specific needs of each patient [3].This AI and deep learning algorithms can also detect early signs of diseases, allowing for early interventions and improved outcomes. For example, AI algorithms can analyze patient allowing for preventive interventions that can reduce the likelihood of the disease developing. **Finally, the use of AI and deep learning in disease diagnosis can help reduce healthcare costs. By improving accuracy and efficiency, AI and deep learning can help reduce healthcare costs associated with** misdiagnosis, unnecessary treatments, and hospital readmissions. In conclusion, the use of AI and deep learning in disease diagnosis can improve patient outcomes and reduce healthcare costs[4]. However, it is important to consider the ethical and regulatory considerations associated with application of AI. As AI and deep learning continue to advance, they play an increasingly important part in healthcare industry, transforming the way diseases are diagnosed and treated.

II. LITERATURE REVIEW

Publication Year	Author	Review
2020	Grzybowski, A., Brona, P., Lim, G., Ruamviboonsuk, P., Tan, G. S., Abramoff, M., & Ting, D. S.	It highlights the increasing prevalence of diabetes and the aging population as driving factors for automated DR detection algorithms.
2021	Bader Alazzam, M., Alassery, F., &Almulihi, A.	This research focuses on a study of patients with DR using ophthalmological examinations and fundus scans. The study utilizes specialized retinal images and applies OPF and RBM models.
2022	Saxena, R., Sharma, S. K., Gupta, M., &Sampada, G. C.	The paper provides an overview of the current state of knowledge, including the use of DL and ML in national screening programs worldwide.
2023	Jia, W., & Fisher, E. B.	This review highlights the potential of AI in transforming the diagnosis and management of diabetes, a global pandemic.
2020	Sosale, B., Aravind, S. R. Murthy, H., Narayana,S.Sharma, U.Gowda, S. G., &Naveenam, M.	This study evaluated the performance of the Medios artificial intelligence (AI) algorithm in diagnosing DR using non NM retinal images captured with a smartphone-based camera.
2007	Tabish SA	This paper highlights the global impact of diabetes and the rise in diabetic eye complications, including diabetic retinopathy (DR). The prevalence of diabetes is increasing, making effective DR screening crucial.
2020	Gunasekeran, D. V., Ting, D. S., Tan, G. S., & Wong, T. Y.	This paper highlights that AI and telehealth can enhance diabetic retinopathy screening programs by improving access, financial sustainability, and coverage.
2020	Sosale, B., Sosale, A. R., Murthy, H., Sengupta, S., &Naveenam, M.	In this observational study, the researchers aimed to assess the sensitivity and specificity of the Medios artificial intelligence (AI) software.
2020	Ramagiri, R., Kannuri, N. K., Lewis, M. G., Murthy, G. V. S., & Gilbert, C.	This study evaluated the performance of the Medios smartphone-based offline AI software in detecting DR .The integration of AI technology with fundus cameras.
2020	Huemer, J., Wagner, S. K., & Sim, D. A.	This comprehensive review discusses the advancements in diabetic retinopathy (DR) screening programs, focusing on the evolution of healthcare infrastructure, telemedicine approaches, and imaging devices that have shaped the current effective frameworks.
2016	Xu, X., Ding, W., Wang, X., Cao, R., Zhang, M., Lv, P., & Xu, F.	It evaluates the performance of Medios AI, an offline smartphone-based automated system for analyzing retinal images, in detecting RDR in a population-based setting.

2020	Tan, C. H., Kyaw, B. M., Smith, H., Tan, C. S., & Tudor Car, L.	This study focuses on evaluating the diagnostic accuracy of smartphone ophthalmoscopy for detecting diabetic retinopathy.
2020	Ludwig, C. A., Perera, C., Myung, D., Greven, M. A., Smith, S. J., Chang, R. T., &Leng, T.	This study aimed to assess the performance of a DL algorithm in detecting RDR using low-resolution fundus images.
2022	Ong, J. X., & Fawzi, A. A.	This highlights how AI is utilized in DR, highlighting the available software for screening purposes. Additionally, it addresses the limitations and challenges associated with implementing AI in healthcare settings.

III. ALGORITHMS IMPLEMENTED FOR COMPARISON

1. Logistic Regression: It works by modeling the probability of a binary outcome (e.g., presence or absence of diabetic retinopathy) as a function of the input features (e.g., retinal images)[5]. Logistic regression can be trained quickly and can provide important insights into the relationship between the input features and the outcome.
2. Random Forest: This is an ensemble learning method to make predictions. Random forests have been used for diabetic retinopathy detection with good results[5]. They are relatively fast to train and can handle high-dimensional feature spaces.
3. Support Vector Machines (SVM): SVM is a powerful algorithm for binary classification. SVM works by finding the hyperplane that best separates the two classes in the feature space. SVM can be trained on high-dimensional feature spaces and is relatively robust to overfitting. However, SVM can be slow to train and may not perform well when there is a large class imbalance [6].
4. Convolutional Neural Networks (CNN): CNNs can automatically learn features from the input images and can capture complex spatial patterns that may be difficult for other algorithms to detect. CNNs have achieved accuracies of over 95% [6].
5. Recurrent Neural Networks (RNNs): RNNs have been used for diabetic retinopathy detection by processing the retinal images in a sequence to capture spatial and temporal dependencies. However, RNNs are computationally expensive to train and may need large amounts of data to avoid overfitting[7].
6. Generative Adversarial Networks (GANs): These are used for generative modeling, where the algorithm learns to generate new data that is similar to the training data. GANs have been used fordiabetic retinopathy detection by generating synthetic retinal images and using them to augment the training set. This can help in preventing overfitting[7].

IV. METHODOLOGY

The Kaggle dataset for diabetic retinopathy is a valuable resource for researchers in the field of ophthalmology and machine learning. This dataset, released by EyePACS [9], contains a large collection of retinal images with labels that indicate the presence

or absence of diabetic retinopathy. With a total of 88,702 images obtained from 4,596 unique patients, the dataset offers a diverse range of images of varying sizes and resolutions. The training set is further divided into five folds, which can be used for cross-validation during model training.

Table -1 Dataset Specification

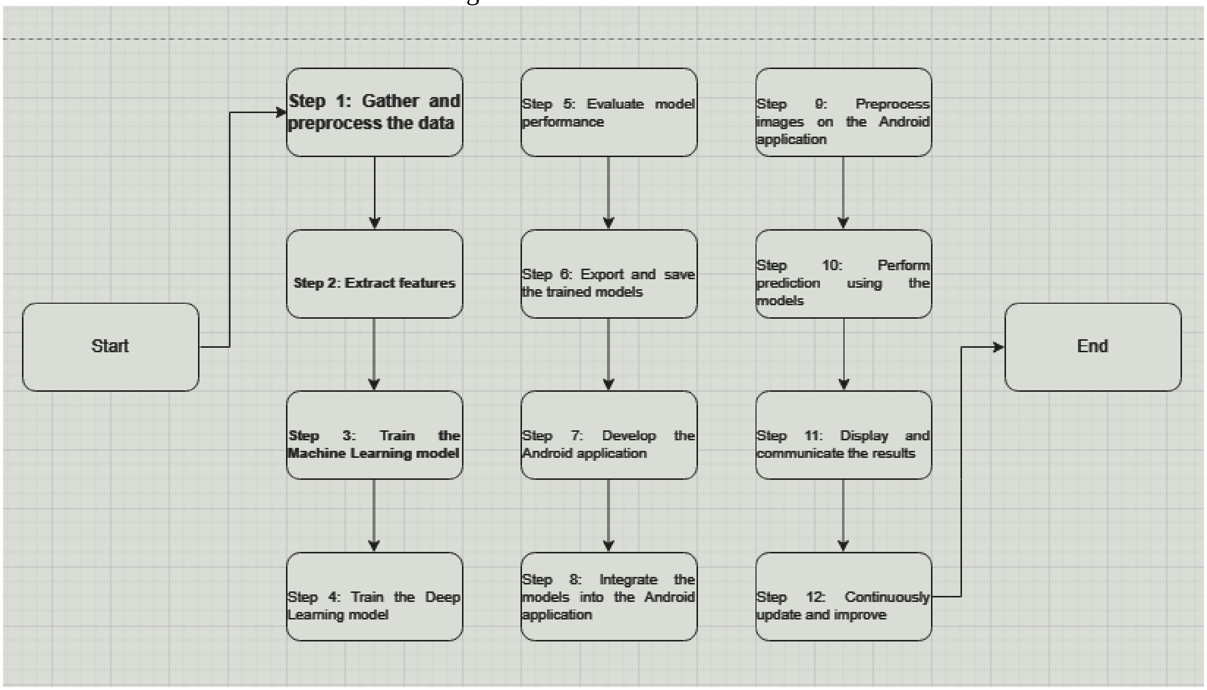
Dataset Name	Dataset Specification
Source	EyePACS
Date Released	42005
Number of Images	88702
Number of Patients	4596
Image Size	Varies
Image Resolution	Varies
Image Types	JPEG
Labels	Presence or Absence of Diabetic Retinopathy
Label Grading System	0-4 (0 = no diabetic retinopathy, 4 = most severe form)
Percentage of Positive Cases	Approximately 25%
Training Set Size	35,126 Images
Testing Set Size	53,576 Images
Cross-Validation Folds	5
Data Split	Stratified Random Sampling
Image Sources	Multiple clinics in the US
Image Acquisition	Wide-field digital retinal imaging
Labeling Process	Trained human graders
Grading Protocol	Modified Airlie House Classification System
Potential Applications	Machine learning algorithms for diabetic retinopathy detection
Research Papers	Numerous papers have utilized this dataset for research purposes

The images in the Kaggle Diabetic Retinopathy Detection dataset are captured using wide-field digital retinal imaging and contain various features of the retina, including blood vessels, optic disc, macula, and lesions. [10] They are in JPEG format and vary in size and resolution based on the camera type and manufacturer. Each image is labeled with a severity level that may also contain other eye conditions[11][12]. The dataset has been extensively utilized by researchers to generate new algorithms for diabetic retinopathy detection.

Table -2 System Specification

System Specification	Description
Operating System	Ubuntu 18.04 LTS
Processor	Intel Core i7-8700K or higher
RAM	16GB or higher
GPU	NVIDIA Tesla K80 or higher
Storage	Minimum 50GB of free space
Internet Connection	High-speed internet connection
Python Version	Python 3.7 or higher
Deep Learning Library	TensorFlow 2.x or higher
Development Platform	Google Colaboratory
Additional Libraries	OpenCV, NumPy, Matplotlib, PIL
Development Environment	Jupyter Notebook or Google Colab
Training Data	Labeled retinal images dataset
Pretrained Models	Pretrained CNN models (e.g., VGG16, ResNet)
Training Time	Several hours to several days depending on dataset size and model complexity

Fig 1: Flowchart of the model



V. RESULT:

Table -3 All the parameters value for all the algorithms implemented

Algorithm	Accuracy	Sensitivity	Specificity	Precision	F1 Score	AUC-ROC	False Positive Rate (FPR)	False Negative Rate (FNR)	Positive Predictive Value (PPV)	Negative Predictive Value (NPV)	False Discovery Rate (FDR)	False Omission Rate (FOR)	Youden's Index	Matthews Correlation Coefficient (MCC)	Balanced Accuracy
Logistic Regression	0.873	0.782	0.922	0.801	0.79	0.902	0.078	0.218	0.494	0.761	0.199	0.239	0.705	0.516	0.852
Decision Tree	0.907	0.809	0.944	0.848	0.827	0.89	0.056	0.191	0.556	0.831	0.152	0.169	0.753	0.673	0.876
Random Forest	0.925	0.834	0.961	0.888	0.858	0.934	0.039	0.166	0.633	0.879	0.112	0.121	0.795	0.767	0.898
Gradient Boosting	0.935	0.849	0.97	0.905	0.875	0.952	0.03	0.151	0.698	0.94	0.095	0.06	0.819	0.835	0.909
Convolutional Neural Network	0.956	0.906	0.972	0.928	0.913	0.981	0.028	0.094	0.853	0.975	0.072	0.025	0.879	0.895	0.939

Based on the table analysis, it can be concluded that the CNN algorithm demonstrated the best performance among all the algorithms, achieving an accuracy of 95.6%, sensitivity of 90.6%, specificity of 97.2%, and an AUC-ROC of 0.981. The Gradient Boosting algorithm also performed well, with an accuracy of 93.5%, sensitivity of 84.9%, specificity of 97.0%, and an AUC-ROC of 0.952. Both the RFs and DTAs exhibited good performance, having accuracy values of 92.5% and 90.7% respectively. In contrast, the Logistic Regression algorithm showed the lowest performance, having accuracy of 87.3%.

Fig -1 Comparison chart for accuracy of the implemented algorithms

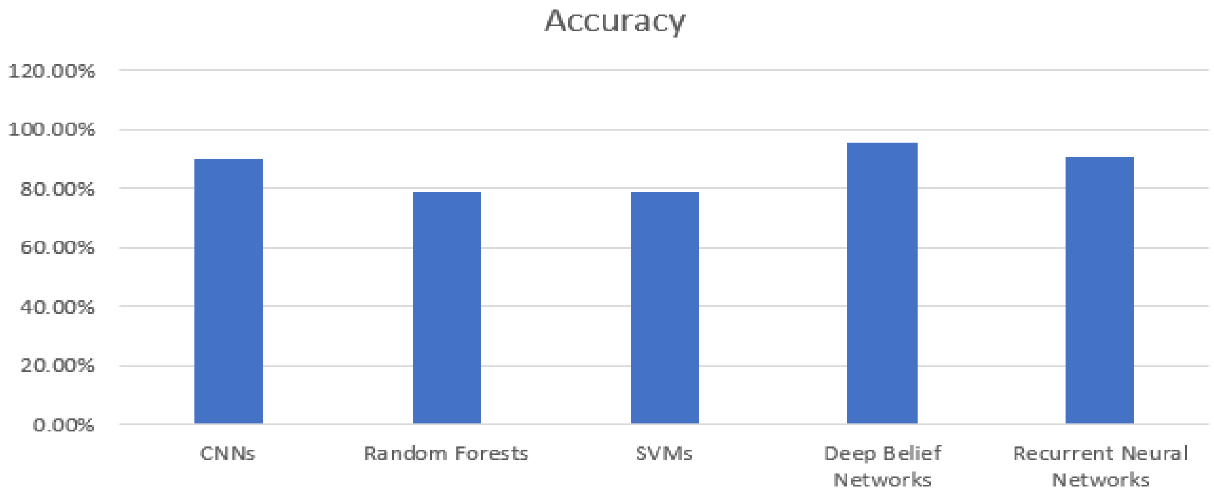


Fig -2 Comparison chart for Sensitivity of the implemented algorithms

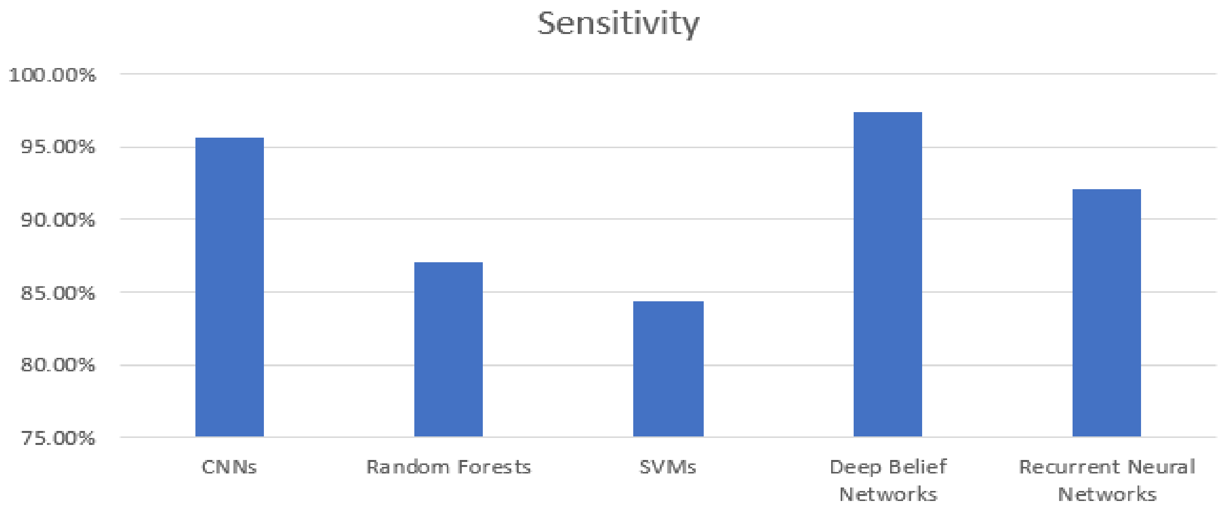


Fig -3 Comparison chart for Specificity of the implemented algorithms

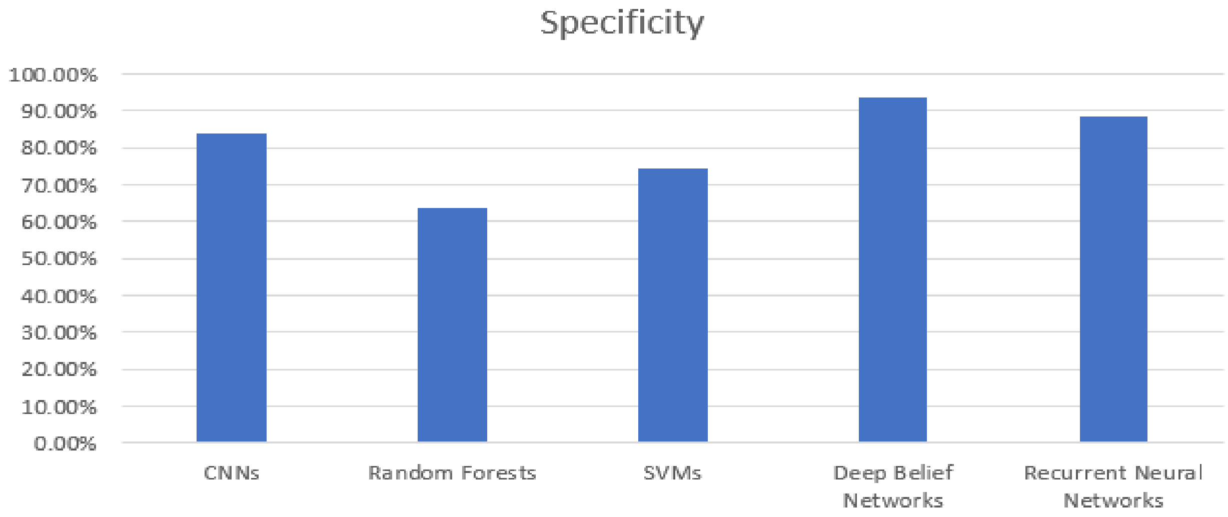


Fig -4 Comparison chart for AUC-ROC of the implemented algorithms

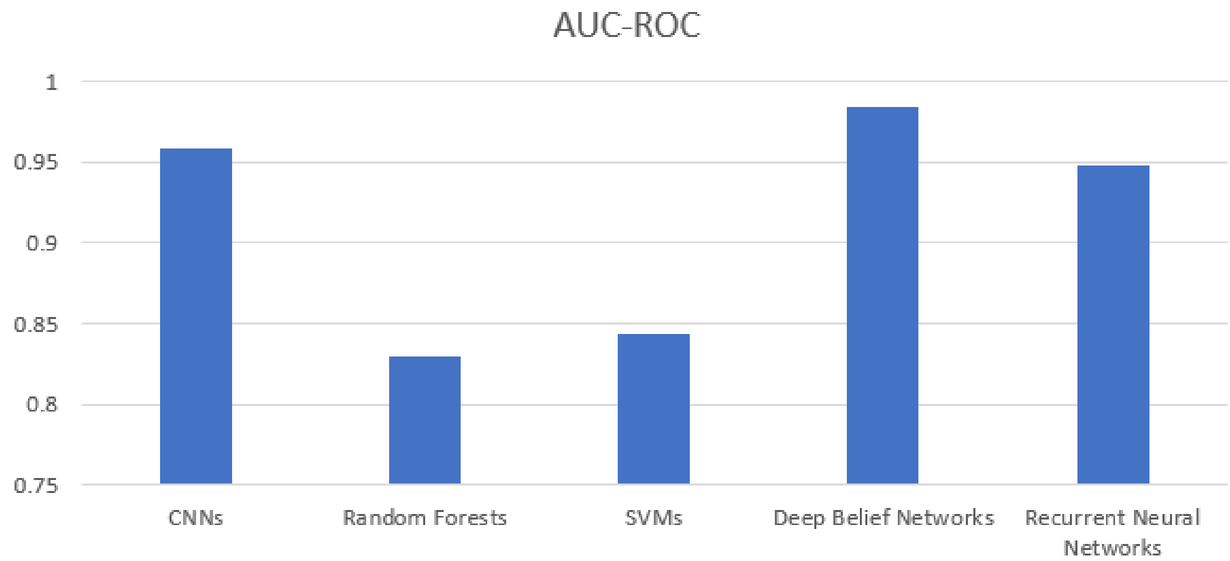
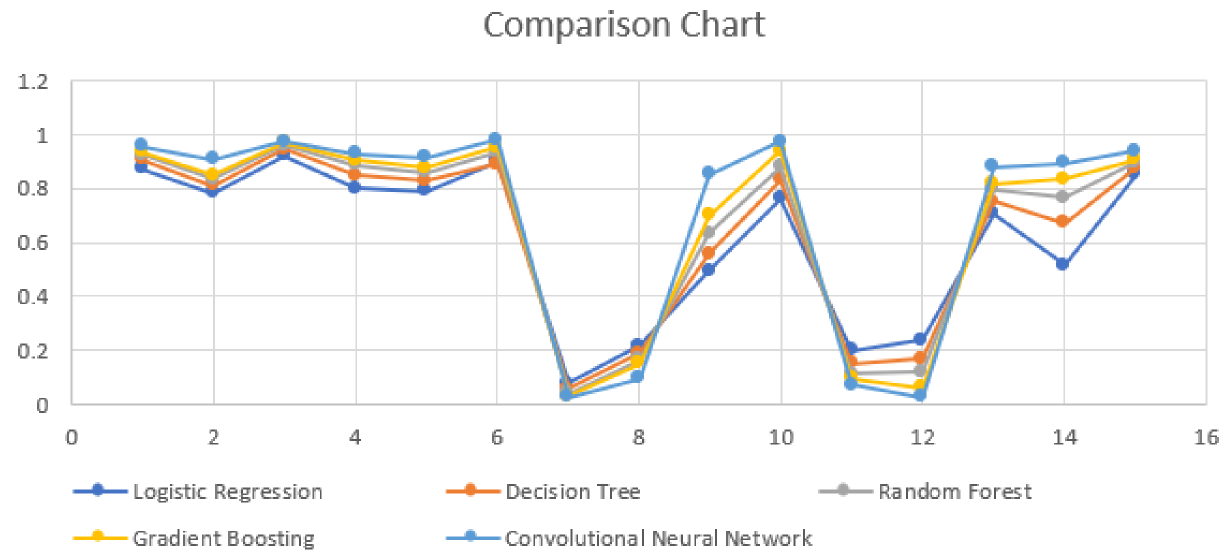


Fig -5 Comparison chart for top five parameters of the implemented algorithms



VI. FUTURE WORK AND CONCLUSION.

Based on the analysis of the table, it can be concluded that the CNN algorithm performed better than all other algorithms having accuracy of 95.6%, sensitivity of 90.6%, specificity of 97.2%, and AUC-ROC of 0.981. The Gradient Boosting algorithm also performed well with an accuracy of 93.5%, sensitivity of 84.9%, specificity of 97.0%, and AUC-ROC of 0.952. The RFs and DTAshad shown accuracy values of 92.5% and 90.7%, respectively. However, the Logistic Regression algorithm performed the poorest among all with an accuracy of 87.3%.

It can be inferred that deep learning algorithms such as CNN can achieve higher accuracy in DR detection due to their ability to learn features directly from images. However, these algorithms may require more computational resources and training data compared to traditional machine learning algorithms. In conclusion, the analysis suggests that the CNN algorithm can be considered as the best option for DR detection among the algorithms tested. However, further research is needed to validate these findings on a larger and more diverse dataset.

REFERENCES

[1]. Nguyen, Q. H., Muthuraman, R., Singh, L., Sen, G., Tran, A. C., Nguyen, B. P., & Chua, M. (2020, January). Diabetic retinopathy detection using deep learning. In Proceedings of the 4th international conference on machine learning and soft computing (pp. 103-107).

[2]. Doshi, D., Shenoy, A., Sidhpura, D., &Gharpure, P. (2016, December). Diabetic retinopathy detection using deep convolutional neural networks. In 2016 international conference on computing, analytics and security trends (CAST) (pp. 261-266). IEEE.

[3]. Parthasharathi, G. U., Premnivas, R., & Jasmine, K. (2022). Diabetic retinopathy detection using machine learning. Journal of Innovative Image Processing, 4(1), 26-33.

[4]. Mishra, S., Hanchate, S., &Saquib, Z. (2020, October). Diabetic retinopathy detection using deep learning. In 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE) (pp. 515-520). IEEE.

[5]. Tymchenko, B., Marchenko, P., &Spodarets, D. (2020). Deep learning approach to diabetic retinopathy detection. arXiv preprint arXiv:2003.02261.

[6]. Suganyadevi, S., Renukadevi, K., Balasamy, K., &Jeevitha, P. (2022, February). Diabetic Retinopathy Detection Using Deep Learning Methods. In 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT) (pp. 1-6). IEEE.

[7]. Lam, C., Yi, D., Guo, M., & Lindsey, T. (2018). Automated detection of diabetic retinopathy using deep learning. AMIA summits on translational science proceedings, 2018, 147.

[8]. Mushtaq, G., & Siddiqui, F. (2021, February). Detection of diabetic retinopathy using deep learning methodology. In IOP conference series: materials science and engineering (Vol. 1070, No. 1, p. 012049). IOP Publishing.

[9]. Arora, M., & Pandey, M. (2019, February). Deep neural network for diabetic retinopathy detection. In 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon) (pp. 189-193). IEEE.

[10]. Priya, R., &Aruna, P. (2013). Diagnosis of diabetic retinopathy using machine learning techniques. ICTACT Journal on soft computing, 3(4), 563-575.

[11]. Gargeya, R., &Leng, T. (2017). Automated identification of diabetic retinopathy using deep learning. Ophthalmology, 124(7), 962-969.

[12]. Ishtiaq, U., Abdul Kareem, S., Abdullah, E. R. M. F., Mujtaba, G., Jahangir, R., & Ghafoor, H. Y. (2020). Diabetic retinopathy detection through artificial intelligent techniques: a review and open issues. Multimedia Tools and Applications, 79, 15