A Pilot Study of Automated Predictive Models for Retinal Diseases

Oboro, Enifome[1]; Akazue, Maureen[2]

[1]Department of Computer Science, Delta State University of Science & Technology, Ozoro, Nigeria

[2]Department of Computer Science, Delta State University Abraka, Nigeria

Publication Date: 2025/08/16

Abstract: Diabetic retinopathy, glaucoma, Central Serous Retinopathy (CSR), age-related macular degeneration (AMD), and retinitis are primary causes of visual diseases worldwide. As such, several types of retinal disease predictive or diagnostic models are designed to prevent vision loss or impairment. Since correct prediction is crucial for treatment, a survey of existing retinal disease predictive or diagnostic models was conducted, and algorithms used to predict retinal disease were analyzed. The survey showed that despite improvements with the incorporation of machine learning, many automated retinal disease diagnosis systems still rely heavily on traditional models for classification tasks. Thus, limiting the retinal disease SVM models' performance in handling complex, high-dimensional retinal images. Therefore, this study incorporates a Convolutional Neural Network-based framework to directly learn discriminative features from raw retinal images without manual intervention to predict kinds of retinal diseases. In the future, the efficiency of this approach will be demonstrated by developing and implementing a CNN-based retinal disease predictive system for diabetic retinopathy, glaucoma, CSR, AMD, and retinitis, and evaluating it for real-world clinical use.

Keywords: *Retinitis, Central Serous Retinopathy, Retinal Diseases, Machine Learning, Convolutional Neural Network.*

How to Cite: Oboro, Enifome; Akazue, Maureen (2025). A Pilot Study of Automated Predictive Models for Retinal Diseases . *International Journal of Innovative Science and Research Technology,* 10(8), 423-430. https://doi.org/10.38124/ijisrt/25aug280

I. INTRODUCTION

Advances in technology have offered solutions, forecast the occurrence of events, and improve the living standard for humans ([1] - [4]). Several works ranging from security ([5] - [10]); preemptive ([11] - [14]); forecast models ([15] – [17]); IoT devices ([18] - [24]); education and business models ([25] - [28]) have being designed to solve or mitigate problems.

Furthermore, recent advancements in disease prediction use technology and machine learning to solve human challenges ([29] [30], and the design of automated disease diagnosis has witnessed advancements with the integration of machine learning techniques. All aspects of medical diagnostic and predictive systems have been developed ([31] - [33]), and retinal diseases are one of such ([34] - [37]).

Retinal diseases cause vision loss, and with the rising utilization of OCT in medical science, automated predictive system holds great potential for reliably and successfully detecting retinal diseases. Hence, several types of retinal disease predictive or diagnostic models are designed to significantly prevent permanent vision loss [38]. Since correct prediction is crucial for treatment, this paper surveyed existing retinal disease predictive or diagnostic models, and algorithms used were analyzed to expose their flaws and introduce a CNN-based framework that directly learns discriminative features from raw retinal images without manual intervention to forecast different types of retinal diseases such as CSR, AMD, diabetic retinopathy (DR), glaucoma, and retinitis.

II. LITERATURE REVIEW

[39] developed a model that applied deep learning to diagnose the retinal sickness condition, with goals to eliminate diagnostic errors from manual image scrutiny and enhance efficiency and accuracy for medical professionals. Future initiatives include developing an online OCT image diagnosis tool and improving model performance with hybrid algorithms like VGG-16 and ResNet-50.

[40] automated the identification of retinal disease using support vector machine that analyzes OCT images and fundus image. The SVM models' performance in handling complex, high-dimensional retinal images is limited compared to deep learning models like CNNs. The developed SVM based algorithm effectively detects the central serous retinopathy, and does not integrate real-time image acquisition and instant prediction functionality.

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25aug280

Another study trained their model on 84,568 retinal OCT images from publicly accessible sources representing the four disease types. The developed model was not trained with fundus photography image, and UFI fundus imaging [41].

[42] conducted a comprehensive review on Retinal Disease Detection. They automated the grading of eye abnormalities using techniques like DCNNs and ViTs, and evaluated the model using OCT and fundus. Future directions include exploring ensemble CNNs for better performance and improving model explainability for clinical adoption.

[43] applied an Artificial Intelligence for the prediction and Screening of eye diseases and analyzed it using ophthalmological data, particularly fundus images and OCT scans on major retinal diseases like DR and AMD. Challenges included securing large datasets and ensuring reliable AI-driven diagnostic accuracy.

[44] employed a VGGNetn advanced detection of DR using fundus cameras. There was the prevalence of undetected DR cases in remote areas.

[45] reviewed and analyzed models using methods with CNN, SVM and MLP as feature selection and classifier methods. Challenges include the complexity of recognizing disease symptoms.

[46] reviewed and analyzed AI's application in a wide range of retinal illnesses. Challenges in integrating AI into clinical practice include the "black box phenomenon.

[47] provided an exhaustive review of detecting retinal diseases through medical image analysis. The authors surveyed CNNs impact on retinal disease diagnosis, especially in detecting DR, glaucoma, and AMD. However, model generalization in clinical settings were identified for further attention.

[48] applied deep CNNs for separation tasks and classified DR and macular edema using various design structures. Also, [49] [50] reviewed the application of deep learning techniques in medical image analysis,

[51] reviewed various CNN models and pre-processing techniques used for early DR detection.

[52] utilized CNNs to analyze images. However, image resolution, dataset variability, and the necessity to improve model generalizability were identified. [53] further applied the use of CNN in fundus images.

[54] reviewed the performance of different models, including CNNs and Recurrent Neural Networks (RNNs), for detecting various retinal diseases. Their study found that CNNs achieved the highest performance in classification tasks. However, challenges such as the need for a larger diversity of data, improving model interpretability, and reducing the dependency on high-quality labeled datasets were identified.

[55] discussed CNNs, ResNets, and GANs architectures in the predictions of DR, AMD, and glaucoma. Their findings suggest that deep learning has significantly improved diagnostic accuracy, but challenges such as overfitting, lack of clear understanding remain significant hurdles.

[56] reviewed various CNN architectures and their effectiveness in detecting DR and AMD. Their findings indicated that CNNs has improved classification accuracy. However, they noted the lack of standardized datasets.

[57] explored the use of deep convolutional neural networks (CNNs) for the early diagnosis of retinal diseases. Their findings showed that CNNs can effectively detect early signs of diseases such as DR and AMD. However, challenges relating to data labeling, and computational complexity during model training were identified.

[58] reviewed deep learning techniques for retinal disease detection using OCT images. However, the complexity of OCT image interpretation was noted.

[59] discussed the use of various models for retinal imaging, including CNNs and hybrid models. The findings suggest that deep learning improves diagnostic accuracy, especially in detecting retinal diseases. However, computational costs were the challenge identified.

[60] and [61] reviewed and evaluated various CNN-based methods and discussed their performance. The findings revealed that CNNs provide high accuracy in detecting diabetic retinopathy. However, challenges such as dataset imbalance, and lack of interpretability, were identified.

[62] surveyed different architectures of CNNs used for detecting diseases such as DR, AMD, and glaucoma. The findings established that CNNs have improved early predictive capabilities.

Several authors ([63] - [68]) highlighted various CNN-based models and their performance in detecting DR and AMD. They found that deep learning techniques have demonstrated significant potential for prediction accuracy. However, the need for specialized expertise to interpret results, ensuring model robustness in clinical environments, and overcoming the complexity of OCT image analysis were highlighted.

[69] study focused on the local binary pattern, SVM and KNN classifiers were used for images dataset classification. The gap identified was missed classification.

[70] developed an AI-based multi-label classification model. Their SURF-GBC model outperformed the conventional methods which are time-consuming and require expert intervention.

[71] developed an automated deep learning-based system for diagnosing retinal diseases using UFI, which offer a comprehensive view of critical ocular structures. The method used involves image pre-processing, data augmentation, and classification using ResNet152, Vision

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25aug280

Transformer. The Key challenges include automating diagnosis while maintaining precision, with the system effectively reducing the need for manual interpretation.

[72] developed an automated system for classify multiple eye illnesses. The method used includes image pre-processing and a Multilevel Glowworm Swarm CNN. This study demonstrated that CNN usage is required in retinal disease early prediction.

[73] improved retinal disease prediction by introducing a hybrid model and a web-based diagnostic tool. The method used is the development of RetiNet, a fusion model combining ResNet50 and DenseNet121, trained on retinal dataset. However, the addition of a web application will enhance clinical usability and decision support for ophthalmologists.

[74] study automated a classification method leveraging on fine-tuning techniques to enhance accuracy while maintaining computational efficiency. The study highlighted its potential for clinical integration and its superiority over other ensemble methods.

[75] proposed a diagnostic CNN support system to detect twelve major retinal conditions. Findings are that retinal disorders have similar manifestations, making manual diagnosis complex. The proposed multi-class classification model proved its utility as a theragnostic tool in ophthalmology.

[76] study enhanced the detection of Choroidal Neovascularization and other causes of eye problem using deep learning techniques. The method used involved preprocessing OCT retinal images and training of multiple CNN models with varying hidden layer configurations for classification into four disease categories.

[77] also proposed the use of AI tools. They advocated for a design approach that prioritizes transparency and user trust key components for AI integration in real-world medical workflows.

[78] utilized bagging techniques with KNN as base estimator to tackled the problem of misclassified cataracts and wrong cataract prediction, which can result in incorrect treatments and wasted resources. Their research challenges include the difficulty in quickly detecting and accurately classifying cataracts, even for experienced opticians.

[79] applied CNN to extract features, detect and differentiate between retinal diseases. Challenges include ensuring model reliability in detecting various retinal diseases from OCT images.

- *Summary of Previous works, Achievements and Knowledge Gap*

Several work on using CNN Model to Classify OCT Images were carried out ([80] - [81]). Different datasets were employed when using deep learning ([82] - [83]). But, some of the existing systems did not integrate real-time image acquisition and instant prediction functionality, making it less practical for immediate clinical application or live screenings. Furthermore, the models that used SVM requires manual feature extraction, which may miss complex patterns that a deep learning model like CNN could automatically learn from raw images. Several other models that used deep learning were restricted to detecting types of retinal disease using either OCT images or Fundus images, or image captured via webcam, limiting its usefulness in diagnosing multiple retinal diseases simultaneously.

The new proposed model is designed to precisely detect and categorize six retinal conditions, namely DR, Glaucoma, Central Serous Retinopathy, Age-related Macular Degeneration (AMD), Retinitis, and healthy eyes, using OCT images, fundus images, and image captured via webcam.

III. RESEARCH METHODOLOGY

The system is designed to use CNN to classify retina conditions into four categories: Normal, CSR, Glaucoma, and DR. This intelligent classification is achieved through a CNN model trained on a labeled dataset of retina images. Analysis of the developed system reveals its effectiveness in improving early diagnosis, reducing dependence on manual screening, and increasing accessibility to ophthalmological care, particularly in under-resourced regions. The core of the system relies on the ability of CNNs to extract visual features, such as blood vessel patterns, and localized lesions from high-resolution images. A graphical interface that allows image capture via webcam is used to enhance usability. The backend utilizes the TensorFlow/Keras frameworks for training and prediction.

The method employed in the design of the retinal disease prediction model is based on a CNN that can process and analyze visual imagery.

- *The CNN Architecture Model Consists of Several Key Layers (see figure 1):*

- *Convolutional Layers:*

These layers apply learnable filters to extract important patterns like blood vessel structure, optic disc features, and pathological anomalies.

- *Activation Function (ReLU):*

Introduced to add non-linearity and ensure better learning.

- *Pooling Layers (MaxPooling):*

For reducing spatial dimensions, preventing overfitting, and enhancing computational efficiency.

- *Fully Connected Layers:*

For mapping the extracted features to the corresponding output disease classes.

- *Softmax Output Layer:*

Produces the final probability distribution over the four target classes.

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25aug280

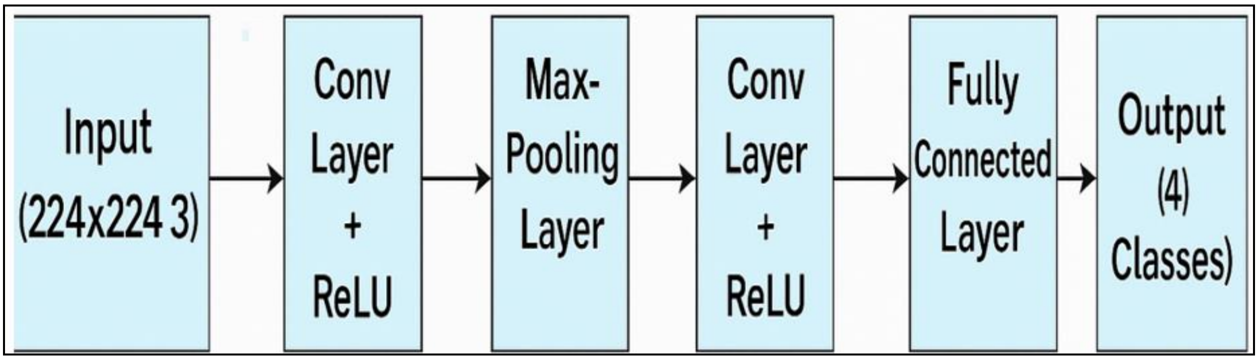

Fig 1 CNN Architecture

IV. RETINAL DISEASE CLASSIFICATION PROCESS

In this retinal disease classification system, the classification is typically done using a Convolutional Neural Network (CNN). Here's how it works for your system (see figure 2):

- *CNN Architecture:*

The CNN is used to automatically learn various patterns and structures related to conditions like glaucoma, diabetic retinopathy, Central Serous Retinopathy, and normal retina.

- *Model Training:*

- CNN model is trained with labeled data (images of retina from the four categories: Normal, Glaucoma, Diabetic Retinopathy, Central Serous Retinopathy).

- During training, the model learns to associate the features extracted from the images to their corresponding category.

- *Classification Process:*

Once trained, CNN model will classify new retina image (e.g., whether it's Normal, Glaucoma, Diabetic Retinopathy, or Central Serous Retinopathy). The CNN typically does this by passing the image through figure 1 and then outputting a probability distribution for each class to enable selection of highest probability distribution.

- *Activation Function:*

The softmax activation function is used to ensure that the output is a probability distribution over the classes.

The high-level architecture of the developed model in Figure 2 provides an overview of key components. It illustrates how data flows from image capture, through preprocessing, to prediction using CNN. This model highlights the integration of automated retinal disease classification and prediction.

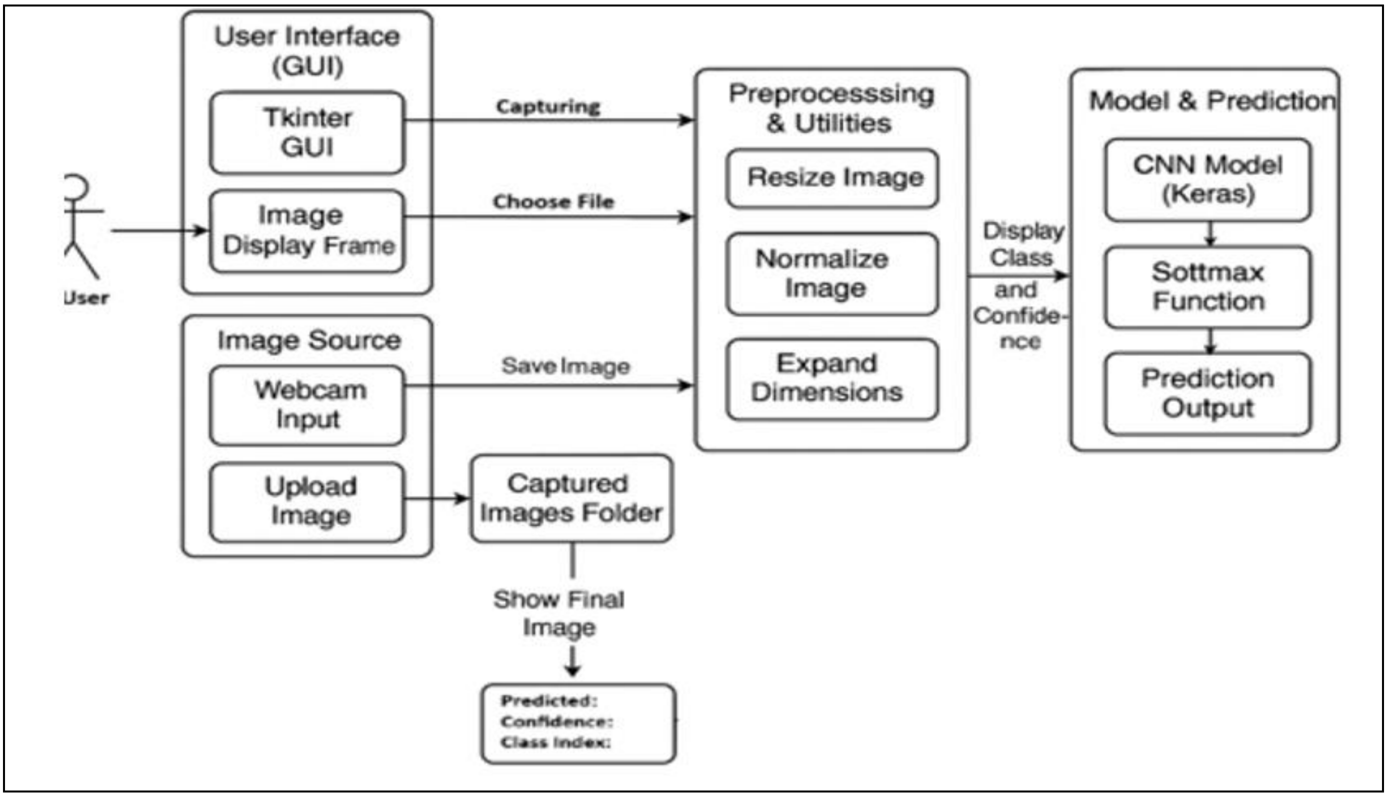

Fig 2 High Level Architecture of the Developed System

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25aug280

V. CONCLUSION

The features of the incorporated components used in the proposed model will significantly enhances detection accuracy, operational efficiency, and scalability for real-world clinical use because of their functionalities.

In this study, the combination of the CNN component into the Retinal disease framework has addressed the problem of SVM models' performance in handling complex, high-dimensional retinal images and provided multiple ways to collect images. The future work will discuss the implementation and evaluation of this model.

REFERENCES

[1]. Kumar, A.S. Tewari, J.P. Singh, Classification of diabetic macular edema severity using deep learning technique. Res. Biomed. Eng. Vol 38, pp 977–987, 2022

[2]. Maureen, E.K. Henry, C. Asuai, Application of RFM model on Customer Segmentation in Digital Marketing. Nigerian Journal of Science and Environment, vol 22, No 1, 2024, 57–67. https://doi.org/10.61448/njse221245

[3]. M. D. Okpor, F. O. Aghware, M. I. Akazue, A. A. Ojugo, F. U. Emordi, C. C. Odiakaose, R. E. Ako, V. O. Geteloma, A. P. Binitie, P. O. Ejeh, Comparative Data Resample to Predict Subscription Services Attrition Using Tree-based Ensembles, Journal of Fuzzy Systems and Control, vol. 2, no 2, 2024, 117-124, DOI: 10.59247/jfsc.v2i2.213

[4]. A.I Maureen and A.I Ben, "Fuzzy based enhanced smart rest room automated faucet system", I.J. Engineering and Manufacturing., vol. 3, 2017, pp 20-30

[5]. M. Akazue and B. Ojeme, "Building Data Mining For Phone Business", Oriental journal of computer science and technology: An international open access peer reviewed research journal, vol. 7, no. 03, 2014, pp. 316-322

[6]. U.K Okpeki and E.U. Omede, Design and implementation of auto tech resource sharing system for secondary schools in delta state. Journal of the Nigerian Association of Mathematical Physics, vol. 51, 2019, pp 325 – 332

[7]. M. Akazue, B. Ojeme, NO Ogini, User interface adaptability for all users International Journal of Natural and Applied Sciences, vol. 6, issue 1, 2010

[8]. A.A. Ojugo and A.O. Eboka, "Empirical evidence of socially-engineered attack menace among undergraduate smartphone users in selected Universities in Nigeria," International Journal of Advanced Trends in Computer Science and Engineering, vol. 10, no. 3, 2021, pp.2103–2108

[9]. M. I. Akazue, A. Aghaulor, B. I. Ajenaghughrure, Customer's Protection in Ecommerce Transactions Through Identifying Fake Online Stores CSREA Press, 2015 World Congress in Computer Science, Computer Engineering, and Applied Computing, July 27th – 30th, Nevada, USA, pp 52-54

[10]. A.A, Ojugo and D.O. Otakore, Intelligent cluster connectionist recommender system using implicit graph friendship algorithm for social networks, Int. Journal of Artificial Intelligence, vol 9, issue 3, 2020, pp497~506, doi: 10.11591/ijai.v9.i3.pp497~506

[11]. U. K. Okpeki, S. A. Adegoke, and E.U. Omede. Application of Artificial Intelligence for Facial Accreditation of Officials and Students for Examinations. FUPRE Journal of Scientific and Industrial Research. Vol. 6, no. 3, 2022, pp01 – 11

[12]. M. Akazue, and A. Aghaulor, Identification of Cloned Payment Page in Ecommerce Transaction. International Management Review, vol. 11, no. 2, 2015, 70-76.

[13]. S.N. Okofu, C. Asuai, O. Okumoku-Evroro, and M. I. Akazue, Development of an Enhanced Point of Sales System for Retail Business in Developing Countries. Journal of Behavioural Informatics, Digital Humanities and Development Rese vol. 11 no. 5. 2025, Pp 1-24. https://www.isteams.net/behavioralinformaticsjournal dx.doi.org/10.22624/AIMS/BHI/V11N1P1

[14]. S.N. Okofu, The impact of cash scarcity on adoption of banking technology by consumers in Delta State, Journal of Social and Management Sciences. vol. 18, no.1, 2023, pp 15 – 28

[15]. M. I.. Akazue, A Survey of Ecommerce Transaction Fraud Prevention Models. In The Proceedings of the International Conference on Digital Information Processing, Data Mining, and Wireless Communications, Dubai, UAE. 2015, pp 140-146

[16]. A. Ojugo and A. O. Eboka, "Memetic algorithm for short messaging service spam filter using text normalization and semantic approach," International Journal of Informatics and Communication Technology (IJ-ICT), vol. 9, no. 1, 2020, pp. 9–18, Apr. 202 doi: 10.11591/ijict.v9i1.pp9-18.

[17]. N.F. Efozia, S. O. Anigbogu, and K. S..Anigbogu, Development of a hybrid model for enhancing data integration process of business intelligence system. Journal of Basic Physical Research vol. 9., no. 2., 2019, pp 1-16

[18]. E.I. Ihama, M.I. Akazue, E. Omede, D. Ojie, A Framework for Smart City Model Enabled by Internet of Things (IoT). International Journal of Computer Applications (0975 – 8887) vol.185, no.6,2023, pp 6-11

[19]. E.I. Ihama, M.I. Akazue., K. O. OBAHIAGBON, A Survey of Smart City Development and the Role of Internet of Things, FUPRE Journal of Scientific and Industrial Research, vol. 9, no. 1, 2025a, pp 28-37

[20]. M. Akazue, C.U. Agwi, and I.B. Ajenaghughrure, I. B (2017). The interlink between rfid of things and internet of domestic things. sau Science-Tech Journal, vol. 2, no.1, 2017, pp 92-101

[21]. S. Okofu, E. K. Anazia, M. Akazue, C. Ogeh, and I. B. Ajenaghughrure, The Interplay Between Trust In Human-Like Technologies And Integral Emotions: Google Assistant. Kongzhi yu Juece/Control and Decision, vol. 38, Issue 01, 2023, pp 809-828

[22]. S. N. Okofu, Users Service Quality Trust Perception of Online Hotel Room Reservation. SAU Journal of

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25aug280

Management and Social Sciences,vol 3, no.1 & 2, 2018, pp 1-14
[23]. M. I. Akazue, Users' Perception in an Intelligent Automatic Fire Detection System for Developing Countries. Journal of Computer Science and its Applications vol 24, no.2, 2017, pp 111 -119
[24]. M. I. Akazue, A fuzzy based intelligent irrigation system. Science-Tech Journal, vol.1, no.1, 2016, pp12-2
[25]. S. N. Okofu, T. Anning-Dorson, and H. I. Duh Consumer Adoption and Continual Use of E-Vouchers: A Study of the Nigeria Telecommunication, International Research Journal of Multidisciplinary Scope, vol. 06, no. 02, 2025, pp. 330-342, DOI:10.47857/irjms.2025.v06i02.03788
[26]. S. N. Okofu, J. Bisina,O. Okumoku-Evroro, and M. I. Akazue, Cash on delivery risk mitigation CMRR model, Journal of the Management Sciences, vol. 61, no. 9, 2024, pp 142 – 155
[27]. M. I. Akazue, G. E. Izakpa, C. O. Ogeh, E. Ufiofio, A secured computer based test system with resumption capability module. Kongzhi yu Juece/Control and Decision, vol. 38, issue 02, May, 2023, pp 893 – 904
[28]. O. G. Mega, M. I. Akazue, O. Z. Apene, and J. A. Hampo, 2024). Adoption of Blockchain Technology Framework for Addressing Counterfeit Drugs Circulation. European Journal of Medical and Health Research, vol. 2, no. 2, pp 182-196.
[29]. T. Dio, M. I. Akazue, S. N. Okofu, Development of an Online Examination Monitoring System using Zoom, International Journal of Computer Applications, vol. 185, no. 40, 2023, pp 1 -10
[30]. O. C. Ikem, M. I. Akazue, Data misuse and theft protection model in internet of things devices, Scientia Africana, vol. 24, no. 2, 2025, pp 277-282
[31]. D. Ojie, M. Akazue, and A. Imianvan, A Framework for Feature Selection using Data Value Metric and Genetic Algorithm, International Journal of Computer Applications, Vol. 184, Issue 43, 2023, pp 14-21, doi:10.5120/ijca2023922533
[32]. R. E. Yoro, M. D. Okpor, M.I. Akazue, E.A. Okpako, A. O. Eboka, P.O. Ejeh, et al., Adaptive DDoS detection mode in software defined SIP-VoIP using transfer learning with boosted meta-learner. PLoS One vol. 20, no. 6, 2025, pp 1-20, https://doi.org/10.1371/journal. pone.0326571
[33]. F. O. Aghware, M. I., Akazue, M. D. Okpor, B. O. Malasowe, T. C. Aghaunor, E. V. Ugbotu, A. A. Ojugo, R. E. Ako, V. O. Geteloma, C. C. Odiakaose, A. O. Eboka, and S. I. Onyemenem, 2025). Effects of Data Balancing in Diabetes Mellitus Detection: A Comparative XGBoost and Random Forest Learning Approach . NIPES - Journal of Science and Technology Research, vol. 7, no. 1, 2025, PP 1–11. https://doi.org/10.37933/nipes/7.1.2025
[34]. G. Litjens, T. Kooi, B. E. Bejnordi, A. A. Setio, F. Ciompi, M. Ghafoorian, and B. Ginneken, (2017). A survey on deep learning in medical image Medical Image Analysis, vol. 42, pp 60-88. challenges. Journal of Medical Imaging, vol. 28, no. 3, 2017, pp 246-260. https://doi.org/10.1111/jmi.12345
[35]. D. S. W. Ting, L. R. Pasquale, L. Peng, J. P. Campbell, A. Y. Lee, R. Raman, and T. Y. Wong, Artificial intelligence and deep learning in ophthalmology. British Journal of Ophthalmology, vol. 103, no. 2, 2019, pp 167–175
[36]. M.I. Akazue, O. Ovoh, A. Edje, O. Clement, and J. Hampo, An enhanced model for the prediction of Central Serous Retinopathy using bagging techniques. Journal of Healthcare Research, vol. 8, 2023, pp 220–227.
[37]. M. I. Akazue, C Ekpewu, E. Omede, A. E. Edje. Development of a Semantic Web Framework for the Blind, International Journal of Innovative Science and Research Technology, Volume 8, Issue 1, January–2023, pp 1781 – 1789
[38]. X. Li, Y. Wu, and W. Zhang,Deep learning applications in retinal image analysis for disease diagnosis. Journal of Medical Systems, vol. 44, no. 8, 2020, pp 123.
[39]. M. Abeer, M. Ali, and Z. Ahmad, Retina diseases diagnosis using deep learning. Journal of Medical Imaging, vol. 15, no. 3, 2022, pp 134-142.
[40]. C N., Arpitha, N. Revani, P. Archana, T.M. Kavya. SVM based CSR disease detection for OCT and Fundus Imaging. M.Tech. Scholar, CS&E Department, Adichunchanagiri Institute of Technology Chikamagaluru, India. Vol. 10 Issue 08. 2023, pp.385 390
[41]. Amit, S. Ahlawat, S. Urooj, N. Pathak, A. Lay-Ekuakille, and N. Sharma, 2023). A deep learning-based framework for retinal disease classification. Healthcare, vol. 11, no. 2, 2023, pp 212
[42]. L. Stwart, and G. Sterestina, Retinal disease detection using deep learning techniques: A comprehensive review. Journal of Ophthalmology and Vision Science, vol. 12, no. 4, 2023, pp 223-234
[43]. Amit, A., Balla, A., and Johnson, P. (2023). Advances in retinal disease detection using deep learning algorithms. Journal of Medical Imaging Research, 42(4), 456-468
[44]. J. Ayesha, S. Naseem, J. Li, T. Mahmood, M.K. Jabbar, A. Rehman, and T. Saba, Diabetic retinopathy detection using retinal fundus images in remote areas. Scientific Reports, vol. 17, 2024, pp 135
[45]. S. Ahmed, M. Khan, and R. Ali, 2024). Review of eye diseases detection and classification using deep learning techniques. Journal of Medical Imaging and Health Informatics, vol. 15, no. 2, 2024, pp 112-126
[46]. Goutam, M. F. Hashmi, Z. W. Geem, and N.D. Bokde, A comprehensive review of deep learning strategies in retinal disease diagnosis using fundus images. IEEE Access, vol. 10, 2022, pp 57796-57823
[47]. S. A. Barman, and M. Al-Mahmud, A comprehensive survey on deep learning in medical image analysis for retinal disease detection. Medical Image Analysis, vol. 69, 2021
[48]. M. E. H. Chowdhury and N. Sultana, Deep learning-based classification and segmentation of retinal diseases using optical coherence tomography. Healthcare, vol. 8, no. 2, 2020, pp 129

ISSN No: 2456-2165 https://doi.org/10.38124/ijisrt/25aug280

[49]. M. A. Farooq, and M. Abdullah, Deep learning for medical image analysis: A survey. Artificial Intelligence in Medicine, vol. 95, 2019, pp 90-99

[50]. J. A. García and J. M. Ruiz, Deep learning for diabetic retinopathy detection: A systematic review. Journal of Ophthalmology, 2021, pp 1-15

[51]. A. González and A. F. López, Early diagnosis of diabetic retinopathy using deep learning methods: Challenges and solutions. Computers in Biology and Medicine, 2022, pp 144

[52]. J. Hu and Y. Zheng, A deep learning-based approach for the detection of macular degeneration. Biomedical Signal Processing and Control, 2021, pp 63

[53]. A. Aslam, S. Farhan, M. A. Khaliq, F. Anjum, A. Afzaal and F. Kanwal, 2023). Convolutional neural network based classification of multiple retinal diseases using fundus images. Intelligent Automation and Soft Computing, vol. 36, no. 3, 2023, pp 2607–2622

[54]. M. S. Islam, and J. Wang, A survey on retinal disease detection using deep learning algorithms. International Journal of Computer Vision, vol. 128, no. 2, 2019, pp 174-190

[55]. M. Madbouly, F. Mohamed and A. Amer, Deep learning models for retinal disease detection. Journal of Healthcare Informatics Research, vol. 5, no. 3, 2020, pp 234-245.

[56]. Y. Cheng, Y. Zhang and H. Xu, Convolutional neural networks for retinal image classification: A survey. IEEE Transactions on Medical Imaging, vol. 37, no. 7, 2018, pp 1580-1596

[57]. F. Liu, M. and Zhang, A deep convolutional neural network-based approach for early diagnosis of retinal diseases. IEEE Access, vol. 7, 2019, pp 65053-65062

[58]. H. Luo and Y. Zhang, 2020). Retinal disease detection using deep learning algorithms and OCT images: A review. Journal of Ophthalmology and Vision Science, vol. 41, no. 3, 2020, pp 242-256

[59]. J. H. Min, and J. H. Jeong. (2021). Deep learning in ophthalmology: Applications and challenges. Journal of Medical Imaging, vol. 28, no. 6, 2021, pp 497-505

[60]. G. Muhammad and M. Z. Afzal, Deep learning methods for the analysis of retinal images in diabetic retinopathy: A systematic review. Health Information Science and Systems, vol. 9, no. 1, 2021, pp 21

[61]. S. Wang and L. Zhou, Convolutional neural networks for retinal disease diagnosis: Applications and challenges. Journal of Biomedical Optics, vol. 25, no. 4, 2020, pp 1-8

[62]. S. Patel and V. Mistry, 2019). Review of deep learning techniques for early detection of retinal diseases. Journal of Biomedical Science and Engineering, vol. 12, no. 1, 2019, pp 58-74

[63]. J. Song and H. Yu, Deep learning for early diagnosis of retinal diseases: A survey. Pattern Recognition, vol. 112, 2022

[64]. K. Roy and P. Singh, Deep learning applications for retinal disease detection: A systematic review. Journal of Optical Society of America A, vol. 38, no. 4, 2021, pp 709-719

[65]. S. Saxena and D. Hegde, A review on computer-aided diagnosis for retinal diseases using deep learning. Journal of Healthcare Engineering, 2020, pp 1-13

[66]. S. Li and Q. Wang, Automated detection of diabetic retinopathy in retinal fundus images: A review of deep learning-based methods. Medical Image Analysis, vol. 51, 2018, pp 131-146

[67]. S., Mankar, and N. Rout, Automatic detection of diabetic retinopathy using morphological operation and machine learning. ABHIYANTRIKI Int. J. Eng. Technol, vol. 3, no. 5, 2016, 12-19

[68]. Mohamed and M. Marwa, Deep learning-based classification of eye diseases using convolutional neural networks for OCT images. Frontiers in Computer Science, vol. 5, 2024

[69]. Abdillah, A. Bustamam and D. Sarwinda, Classification of diabetic retinopathy through texture features analysis. In Advanced Computer Science and Information Systems (ICACSIS), 2017 International Conference on IEEE, pp. 333-338

[70]. S. Megala, T. S. and Subashini, (2020). An automated multi-retinal disease classification model using machine learning techniques. International Journal of Advanced Research in Engineering and Technology (IJARET), vol. 11. No. 11, 2020, pp 937–958

[71]. T. D. Nguyen, D.T. Le, J. Bum, S. Kim, S. J. Song and H. Choo, Retinal disease diagnosis using deep learning on ultra-wide-field fundus images. Diagnostics, vol. 14, no. 1, 2024, pp 105

[72]. R. Chavan and D. Pete, Automatic multi-disease classification on retinal images using multilevel glowworm swarm convolutional neural network. Journal of Engineering and Applied Science, vol. 71, no. 2, 2024

[73]. N. G. Barai, S. Banik and F. M. J. M. Shamrat, A novel fusion deep learning approach for retinal disease diagnosis enhanced by web application predictive tool. International Journal of Advanced Computer Science and Applications (IJACSA), vol. 14, no. 12, 2023, pp 704–712

[74]. A. Rakib, M/ M. Billah, A. S. Ahamed, H. M. Imamul and M. S. A. Masum, EfficientNet-based model for automated classification of retinal diseases using fundus images. European Journal of Computer Science and Information Technology, vol. 12, no. 8, 2024, pp 48-61

[75]. N. T. Rao, M. Siddique, K. S. Kishore, K. I. Reddy and P. V. Anurag, Retinal disease prediction using machine learning. International Research Journal of Modernization in Engineering, Technology and Science, vol. 7, no. 3, 2025, pp 11828–11835.

[76]. A. Mohammad, A., M. Z. Utso, S. B. Habib and A. K. Das, (2021). Predicting retinal diseases using efficient image processing and convolutional neural network (CNN). Journal of Engineering Advancements, vol. 2, no. 4, 2021, pp 221–227

[77]. S. Sorrentino, L. Gardini, L. Fontana, M. Musa, A. Gabai, A. Maniaci, S. Lavalle, F. D'Esposito, A. Russo, A. Longo, P. L. Surico, C. Gagliano and M. Zeppieri, M. (2024). Novel approaches for early detection of retinal diseases using artificial

intelligence. Journal of Clinical Medicine, vol. 13, no. 1, 2024, pp 42
[78]. Maureen, O. Ovoh, A. Edje, O.\ Clement and J. Hampo, An enhanced model for the prediction of Central Serous Retinopathy using bagging techniques. Journal of Healthcare Research, vol. 8, 2023, pp 220–227
[79]. Mohamed, Deep learning-based classification of eye diseases using convolutional neural networks for OCT images. Frontiers in Computer Science, vol. 5, 2024
[80]. Goutam, M. F. Hashmi, Z. W. Geem and N. D. Bokde, A comprehensive review of deep learning strategies in retinal disease diagnosis using fundus images. IEEE Access, vol. 10, 2022, pp 57796-57823
[81]. Y. Wang, W. Zuo and J. Zhang, Bias in deep learning for medical imaging: Challenges and solutions. IEEE Transactions on Medical Imaging, vol. 43, no. 2, 2023, pp 230-239
[82]. R. Kumar, P. Sharma, S. Gupta and A. Singh, Deep learning approaches for automated retinal disease detection: Challenges and future directions. International Journal of Ophthalmic Research, vol. 16, no. 1, 2024, pp 45-56
[83]. X. Li, Y. Wu and W. Zhang, Deep learning applications in retinal image analysis for disease diagnosis. Journal of Medical Systems, 44, no. 8, 2020, pp 123