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Study on Deep Learning CNNs for Automated Eye Disease Detection Using Retina Scans

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Abstract: Rapid advancements in the industry, especially machine learning (ML) and deep learning (DL), have made automated disease detection a prominent field. These methods have been frequently used to solve biomedical categorization issues, such as the diagnosis of eye diseases. Preventing irreversible vision loss requires early detection of eye conditions; however, manual diagnosis remains a complex and challenging process to scale. To aid in the diagnosis of ocular disease (OD), current research has focused on utilizing ensemble deep learning models based on Convolutional Neural Networks (CNNs). Several networks—EfficientNet, ResNet50, RegNetY040, MobileNetV2, InceptionV3, Xception, and DenseNet201—are used in this study to extract pertinent features and manage the multiclass classification task from a pre-processed dataset of fundus images. The best architecture is determined as a possible remedy for enhancing OD diagnosis after the models are assessed using accuracy and F1-score criteria.

Keywords: Automated Diagnosis, Ophthalmic Issues, Neural Networks.

I. INTRODUCTION

Past few years have witnessed the utilization of AI models based on the principles of ML and DL algorithms in a wide range of areas. They are utilized to different extents of efficiency in the area of diagnosing the disease in the biomedical environment. The paper belongs to a bigger illustration of a biological classification challenge application with the help of a DL model, and examines one of the tasks that a model can accomplish to help identify an ocular disease automatically. It must be noted that ophthalmic sickness encompasses a wide range of anomalies related to the human eye. These can range from mild problems like myopia and hyperopia, which are typical refractive defects, to more serious disorders.

Major concern with treating individuals who have experienced temporary or permanent visual loss is the failure to diagnose these conditions early in the course of the illness. Some of the obstacles to eliminating ophthalmic disease in the general population include a lack of professionals to evaluate patients and administer comprehensive treatment at the right time, as well as a lack of easily approachable & reasonably priced utilities for patients to receive frequent eye exams.

The paper is aimed at proposing the effectiveness of key algorithms to process a resource that comprises a great number of ocular photos and identify its key details. These algorithms are also employed in categorizing a patient's OD in terms of their issues. To do so, the paper examines the use of different CNN-based Deep Learning models that include EfficientNet, ResNet50, RegNetY040, MobileNetV2, InceptionV3, Xception, and DenseNet201 on the already pre-processed data containing more than 10000 fundus images. The case that the patient may possess more than one OD present is also taken into consideration in the study, which has been observed very frequently in real-time data.

It is worth pointing out that although some recent studies being done by peers are exploiting the unsupervised deep learning techniques, as mentioned in [1], the current structure uses the method of employing the techniques that utilize the multi-class tagging in the dataset. The usage of the pre-trained models has been demonstrated by Zamil S. Alzamil [2] in his work, which is also taken into consideration in this work. Overall, the work aims at exploring the above models with regard to the diagnosis of an OD using image processing and the identification of the most efficient algorithms following a comparative analysis.

II. LITERATURE SURVEY

By comparing the patient's symptoms with the relations found in the information used for training, the professionals appear to be using these algorithms to assist in classifying whether or not the patient has a specific ailment. This method has been quite successful, and the well-known DL models that have been used recently, only to diagnose different eye conditions, are mentioned in this section.

To identify different eye diseases, authors in [3] proposed their concept, “Fundus-DeepNet,” which is a combination of multi-label deep learning models. They have also, among others, explored the impacts of extensive image pre-processing that is inclusive of procedures such as scaling of images. The other commendable approach that the authors had adopted in this work to achieve an on-site F1 score of 89.13 percent was data fusion. Also, authors Junjun He, Cheng Li Jin Ye, Yu Qiao, and Lixu Gu have searched the capabilities of deep neural networks in the field of multi-label ocular disease classification [4].

For the same issue, Neha Gour and Pritee Khanna [5] have adopted the strategy where they employed CNNs as per transfer learning. They also looked at the possibility of having several illnesses in one patient; their research found that VGG16, a pre-trained architecture, works best when an "SGD optimizer" is added. In their study [6], Mamoon A. Al Jbaar and Shefa A. Dawwd presented the innovative choice of employing "embedded models for parallel diagnosis of ocular diseases." Two key designs need to be noted: the former makes use of the “VGG16 deep learning network,” while the latter provides a system that integrates the major modern DL techniques. The two models are highly effective in the classification of ophthalmic diseases “with an error of 0.9974 and 0.96, respectively.”

Authors in [7] created a multilayer perceptron with GLCM and LBP feature-extraction methods to develop a recognition system to detect ophthalmic diseases, with accuracy of 99.58 percent on off-site test data. Author in [8] have also employed some very relevant methods in correlation with the aforementioned knowledge. Khalid Mostafa et al. [9] were more conservative and they used the ODIR dataset with well-tuned hyperparameters to achieve high performance in multi-class classification. A different example is the DeepRetino proposed by Fatima Zahra Belharar and Nabila Zrira \[10], which uses Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve image contrast and classify six eye disorders with a modified CNN model to perform effectively in the ODIR dataset.

Other authors, such as in [11], have also highlighted that a person may possess more than one ocular disease simultaneously, and they aimed at the diagnosis of more than one OD. To determine issues using eye pictures available in the dataset, they have suggested a multi-label convolutional neural network (ML-CNN) system according to ML classification (MLC). The model achieved an accuracy of 94.3, making it superior. Authors in [12] have chosen to diagnose Cataracts more directly, employing the three classical frameworks of CNN, Inception V3, and VGG-19 frameworks; their work has found that the latter (0.9587 accuracy) is the dominant one.

As a practical application aspect of the mentioned models, Zhiri Tang and Hau-San Wong have chosen to research the privacy issues and data anomalies of the data needed to support the functions of these OD-detecting models [13]. Their work may be considered a point of departure when implementing the different models in this specific biomedical classification issue. The above-mentioned can be quite useful in expanding upon the developments made by Archana Chaudhary, Shubhankar Joshi, and Pratik Hublikar [14] in which they have employed ensemble techniques to detect ODs and have delivered an excellent accuracy of 83.85 percent through their ensemble model. Another approach of applying transfer learning to suggest Deep Neural Networks has also been implemented by authors Fanyu Du et al [15]. This assisted them in distilling their suggested model but in order to minimize the problems faced. Their conclusions, accuracy of 0.9237 and F-1 of 0.914, indicate a huge improvement in the current percentages that have been achieved in the respective metrics by authors who use alternative methods. Additionally, Daniel Shu Wei Ting et al. [16] provide a summary of the variety found in the many investigations conducted on the use thisI technology in ophthalmology. Although their assessment highlights their shortcomings, such as the models' ambiguous nature, it also highlights how effective the technology is at accurately diagnosing ODs.

In their study [17], Xingyuan Ou et al. reported noteworthy outcomes and suggested BFENet as a model that would be appropriate for the given challenge. To address the problem of "multi-label ophthalmic disease classification," they have used a multifaceted strategy. Using on-site data, their suggested approach produced an F-1 score of 0.886. The difficulty of detecting ocular diseases has been optimized by P. Glaret Subin and P. Muthukannan [18]. To optimize the hyperparameters and train the CNN, they have included an approach known as the "flower pollination optimization algorithm." By using the Multiclass SVM for disease classification, the CNN output was significantly improved.

The research by Chengfeng Zhou et al. [19] also investigated only one disease classification, as it allowed the authors to concentrate their efforts and enhance the research. They explored the effect that feature alignment had on the dataset to diagnose glaucoma with generated values. As a way of resolving the problems found, authors in [20] suggested the use of the Novel Mixture Loss Function. The proposed model has a strong argument on its side as a trustworthy method of OD identification, as it can help treat the issues of the imbalance of classes and outliers.

The severity of complications that arise during pregnancy and the postpartum period varies, ranging from mild pain to conditions that could be fatal for both, the mother and the foetus [21]. Machine Learning (ML) algorithms are the valuable tool for diagnosis/predicting the diseases such as coronary heart disease [22][23], brain tumor [24], pregnancy risk monitoring [25], lung diseases [26] etc., Considering the obstacles faced by public health systems, prompt prenatal care, cognizance of pregnancy risk factors, and availability of medical services are essential for expectant mothers [27]. Preventing and treating fatal maternal health issues requires prompt medical intervention, skilled healthcare providers, and emergency obstetric care. This research suggests applying Machine Learning (ML) algorithms to evaluate a dataset of physical symptoms experienced by expectant mothers and forecast their risk levels. By identifying risks, the approach seeks to facilitate targeted well-being and avoid long-term repercussions like late life depression as well [28]. While routine prenatal care and communication with healthcare providers are crucial, medical professionals can receive early and targeted care based on individual risk levels with the help of precise ML algorithms.

It is evident from the work in [29-31] that Explainable AI (XAI) offers transparent and comprehensible insights that help monitor and predict maternal risk. It improves the comprehension of AI model decisions by healthcare professionals, pinpoints critical factors affecting maternity predictions, and allows risk assessments to be customized based on the unique profiles of mothers.

Assaduzzaman et al. [32] showed the working of ML algorithms RF, DT, CatBoost, XGBoost, and Gradient Boosting to predict the factors that affect maternal health. They concluded that Random Forest, with a performance score of 90%, precision (90%), recall (90%), and F1-score (90%), was the best performing of the five different algorithms they deployed. The authors in [33] also used various computational models to analyse maternal health risks and deduced the alarming rate at which the mortality of women during pregnancy seems to be escalating, further highlighting the necessity of providing targeted obstetric care to pregnant women. Of the six algorithms they implemented, Random Forest, which had an accuracy of 0.858267, was again the best performer.

Unlike the previously mentioned work, the authors in [34] developed a strong ML model as an enhancement of the conventional machine learning algorithms to forecast the level of maternal health risks and achieved an accuracy of 70.21%. Another issue to look forward to in the course of further research is the problem of data security when we proceed to a more feasible version of the implemented solution under consideration, and a solution based on the Blockchain Model can be a viable option for this. The implementation of the latest technology of blockchain in the exchange of maternal health data and risk forecasts can help eliminate the lack of accountability and transparency in the data management in the sphere of obstetic care. Although implementing the machine learning algorithms into the field, as this paper suggests, the integrity of the data must be ensured, and thus, the research by the authors in [35] can be a worthy starting point in that matter.

In [36], the authors have done a thorough study on health data monitoring to decrease maternal, neonatal, and infant mortality rates by applying different models for death risk predictions in the initial phases of gestation itself, based on the available information from Brazilian Public Health Systems regarding the same. Their work further develops an understanding of the efficiency of Random Forest, which again outperforms the rest of the applied algorithms.

In [37], a more specific problem statement in the form of predicting risk level during childbirth is taken, and a Fuzzy predictive model has been used for the same. A Fuzzy predictive model with an accuracy of 88.95% provides a reliable alternative to the problem. Moving ahead, [38] suggests the need for a good system for such care. The work has specific importance when we move from the theoretical aspects of this work to real-world implementation, as doctors need to have an understanding of the ML models before they can adopt them for diagnosis purposes.

Qiao et al. [39] have carried out a thorough analysis to compare and ameliorate the outputs with the reduction of dimensions through a feature ranking strategy. Another concept that is incorporated in their work is the fact that RF is one of the most effective methods of assessing datasets. Recent advancements in quantum machine learning have introduced quantum convolutional neural networks (QCNNs), inspired by classical CNN architectures. Wei et al. [40] proposed a QCNN framework that reduces computational complexity while maintaining robustness to noise, making it suitable for image recognition tasks. Their work demonstrated the application of QCNNs in spatial filtering and handwritten digit recognition, highlighting its potential to accelerate deep learning models. Such innovations indicate the future scope of integrating quantum computing with CNN-based medical imaging, including ocular disease diagnosis, to enhance accuracy and efficiency in large-scale image processing.

Li et al. [41] introduced a method (acronym: QDCNN) leveraging quantum parameterized circuits to address the high computational demands of classical CNNs in image recognition. Their hybrid quantum-classical framework demonstrated efficiency gains and satisfactory accuracy on benchmark datasets such as MNIST and GTSRB. The study highlights the potential of quantum-enhanced CNN models in large-scale medical imaging, including fundus-based ocular disease diagnosis, where computational efficiency and feature extraction are critical.

Youssry et al. [42] came up with a method where each pixel is modeled as a quantum system and evolved under external forces derived from image features. Their method achieved superior performance in segmentation tasks, demonstrating high sensitivity and specificity across synthetic and natural images. Such quantum-inspired approaches highlight the potential of advanced computational models to enhance medical image analysis, including fundus image segmentation for ocular disease diagnosis.

Aburaed et al. [43] gave a detailed review of the quantum theoretical application of image processing with a major focus on key data transformation applications. Their work emphasized how quantum informational models could be used to extrapolate classical image processing methods with better computational efficiency and scalability to big data. Notably, the paper has highlighted the difficulties in the process of classical-quantum transformation and has proved promising increases in performance. This type of quantum-inspired progress offers a platform on which, potentially, can be combined with deep learning and CNNs to achieve even greater ocular fundus image quality analysis and multi-disease diagnosis.

Yuan et al. [44] implemented a quantum image segmentation algorithm based on an adaptive threshold with the NEQR model that was simulated with the IBM Q platform. Using a moving average scheme, the algorithm estimated thresholds of image regions, adapting exponentially to fewer auxiliary qubits than previous quantum segmentation algorithms. Their work shows that it is possible to process complicated quantum image processing tasks such as segmentation and feature extraction. These quantum-inspired approaches can be very helpful in improving fundus image processing, which can be added to CNN-based systems because they can be used to effectively and correctly detect multi-class ocular diseases.

Tacchino et al. [45] proposed a quantum information-based perceptron model, experimentally implemented on a small-scale quantum processor. By leveraging quantum principles, their design demonstrated exponential efficiency in storage and processing over classical neural models. The hybrid quantum-classical training scheme showed promising results in simple classification tasks, serving as a foundational step toward practical quantum neural networks. Advancements like these offer future opportunities to integrate quantum computing with CNN-based models for intensifying fundus image classification in ocular disease diagnosis.

Abel et al. [46] have come forward with a fully quantum-based NN framework trained on a quantum annealer without classical components. By encoding parameters, approximating activation functions, and mapping loss minimization to an Ising Hamiltonian, the model achieved efficient binary classification with fast convergence. Such quantum training methods demonstrate potential for scalable medical image analysis, and could complement CNN-based approaches for multi-class ocular disease detection using fundus images.

In order to enable parallel processing with exponential speedup, Ma et al. [47] devised a quantum edge detection technique that makes use of an enhanced Sobel operator and NEQR image representation. Their method increased the accuracy and versatility of image feature extraction. Improved feature extraction in medical imaging, particularly fundus-based visual disease diagnosis, may be supported by such quantum image processing techniques.

Qiu et al. [48] applied deep quantum neural networks for detecting entanglement, addressing limitations of traditional separability criteria. Their continuous-variable models demonstrated efficiency in complex classification tasks. Quantum-inspired neural architectures like these focuses over future opportunities for intensifying medical image analysis, including multi class ocular disease prediction using fundus photographs.

Table 1: Summary of Ocular Disease Recognition Methods

Ref	Authors	Method / Model	Dataset / Domain	Key Findings
[1]	Vijayalakshmi et al. (2023)	Self-supervised vs. supervised DL	Ocular images	Self-supervised learning is effective with less labeled data
[3]	Al et al. (2024)	FDN (multi-label)	Fundus images	Multi-label detection improved the accuracy for ocular diseases
[4]	He et al. (2021)	Dense correlation DNN	Ocular datasets	Dense correlation improved classification performance
[5]	Gour & Khanna (2021)	Transfer learning CNN	Ophthalmic dataset	Transfer learning boosted multi-label classification
[6]	Al Jbaar & Dawwd (2023)	Embedded DCNN models	Embedded diagnosis system	Parallel diagnosis feasible with embedded CNNs

Ref	Authors	Method / Model	Dataset / Domain	Key Findings
[8]	Chen et al. (2021)	Dense CNN on smartphone images	Smartphone-based ocular images	High accuracy with mobile-captured images
[9]	Mostafa et al. (2023)	CNN for ocular disease classification	Fundus images	Robust CNN classification of multiple diseases
[10]	Belharar & Zrira (2022)	DeepRetino (transfer learning CNN)	Retinal images	Effective ophthalmic classification via transfer learning
[11]	Ouda et al. (2022)	Multi-label DL	Fundus images	Achieved 96%+ accuracy across multiple ocular diseases
[12]	Vayadande et al. (2022)	Basic CNN	Ocular dataset	Demonstrated feasibility of DL for ocular recognition
[14]	Chaudhari et al. (2023)	Ensemble DL techniques	Ocular recognition dataset	Ensemble models enhanced classification accuracy
[15]	Du et al. (2024)	Transfer learning + DS theory	Eye disease dataset	Improved diagnostic confidence with DS theory
[17]	Ou et al. (2022)	BFENet (bilateral fundus CNN)	Bilateral fundus dataset	Two-stream CNN improved multi-label recognition
[18]	Muthukannan (2022)	Optimized CNN	Fundus dataset	Optimized CNN enhanced detection performance
[19]	Zhou et al. (2022)	Feature alignment CNN	Glaucoma fundus images	Improved generalization in glaucoma detection
[20]	Luo et al. (2021)	CNN with mixture loss	Fundus images	Novel loss improved overall classification accuracy

Little et al. [49] evaluated dysphonia measures for telemonitoring Parkinson's disease, introducing Pitch Period Entropy (PPE) to enhance robustness against noise and variability. Utilizing sustained phonations and by guided vector machines, they achieved 91.4% classification accuracy, enhancing advanced features and machine learning to improve medical diagnosis reliability.

Little et al. (2007) brought into the picture nonlinear recurrence and fractal scaling methods to look around for disordered voice signals, taking a glimpse of both aperiodicity and turbulence beyond classical linear tools. Their approach improved classification of pathological voices, under-scoring the importance of nonlinear dynamics for robust biomedical diagnosis [50].

Machine learning has demonstrated exceptional potential in healthcare diagnostics. For instance, Dhyani et al. [51] compared supervised algorithms such as Random Forest, Logistic Regression, SVM, and boosting techniques with SMOTE enhancement for chronic liver disease prediction, achieving high accuracy. This motivates similar applications of deep learning for ocular disease classification.

Machine learning has been applied in early disease prediction, such as diabetes prediction using hyper-parameter tuned XGBoost classifiers on clinical datasets, achieving over 93% accuracy [Gayathri et al., 2022]. [52]These advancements keeps in mind how optimized models can guide similar approaches in fundus-based ocular disease diagnosis via CNN frameworks.

Machine learning has been widely applied in cancer risk prediction. Ganguly et al. [53] compared algorithms including SVM, KNN, RF, DT, and XGBoost for cervical cancer risk classification, achieving up to 99.6% accuracy. Such comparative studies demonstrate how optimized ML models can guide CNN-based ocular disease diagnosis.

Ensemble learning has proven effective in healthcare diagnostics. Patra et al. [54] introduced a two-step hybrid ensemble model with feature selection for coronary heart disease prediction, achieving 95.87% accuracy. Such hybrid strategies inspire similar applications in ocular disease classification using CNNs, where multi-class prediction benefits from feature optimization.

Ensemble learning has shown promise in early disease detection. Tallapureddy and Radha [55] demonstrated that combining models like SVM, KNN, RF, and XGBoost improved Parkinson's disease diagnosis, achieving up to 91% accuracy. Such ensemble strategies can similarly enhance fundus image-based CNN classification for multi-class ocular disease diagnosis.

Quan et al. [56] demonstrated the effectiveness of deep learning in healthcare by employing Bidirectional LSTMs to capture dynamic speech features for Parkinson's disease detection. Their findings highlight how temporal feature learning enhances diagnostic accuracy, paralleling CNN-based approaches for fundus images in ocular disease classification.

Moro-Velazquez et al. [57] evaluated advanced automatic speech recognition (ASR) systems on speech from individuals with Parkinson's disease and observed substantially higher word error rates compared to healthy controls. Their results demonstrate the capability of deep learning models to capture fine-grained pathological patterns in biomedical signals, a concept that can be readily extended to ocular disease diagnosis using fundus image analysis.

Taleb et al. [58] investigated Parkinson's disease detection through handwriting analysis using CNN and CNN-BLSTM architectures, reporting a high accuracy of 97.62% with data augmentation techniques. This study illustrates the strength of deep learning in identifying discriminative characteristics from biomedical data, closely paralleling CNN-based approaches applied to fundus images for ocular disease classification.

Senturk [59] introduced a machine learning framework for early Parkinson's disease diagnosis that combines feature selection with classifiers such as SVM, ANN, and CART, achieving an accuracy of 93.84%. The findings underline the importance of optimized feature sets and computationally efficient models in medical diagnosis, a strategy that is equally relevant for CNN-based fundus image classification in ocular disease detection.

Wang et al. [60] proposed a deep learning approach for early Parkinson's disease identification using premotor features, reaching an accuracy of 96.45% and surpassing the performance of 12 traditional machine learning and ensemble methods. Their comparative analysis highlights the superior robustness of deep learning techniques in biomedical diagnostics, reinforcing their applicability to CNN-driven ocular disease classification using fundus images.

Almeida et al. [61] examined sustained phonation and speech signals for Parkinson's disease detection by employing feature extraction methods alongside machine learning classifiers, achieving accuracies exceeding 94%. Their work emphasizes the benefit of leveraging multiple biomedical signal modalities to improve diagnostic performance, analogous to fundus-based CNN approaches for ocular diseases where diverse feature representations enhance classification robustness.

Tadse et al. [62] utilized data science and machine learning techniques for the early detection of Parkinson's disease, comparing the performance of various algorithms to determine the most reliable predictors. Their study demonstrates how systematic model comparison using biomedical data can strengthen diagnostic outcomes, a principle that is similarly vital in CNN-based fundus image analysis for ocular disease classification.

Narendra et al. [63] explored Parkinson's disease detection using both traditional pipeline approaches and deep learning models trained on speech signals. By leveraging CNN and MLP architectures with glottal and acoustic features, they demonstrated the promise of end-to-end systems, reflecting how CNNs can enhance non-invasive disease diagnostics, including ocular analysis.

Rajeswari and Nair [64] applied CNN–LSTM models on speech features such as jitter, shimmer, and harmonic-to-noise ratio for Parkinson's prediction, achieving 85% accuracy. Their work highlights how hybrid deep learning architectures outperform traditional classifiers, reinforcing CNN's potential for complex biomedical diagnostics, including ocular disease detection using fundus imagery.

Vigneswari and Aravinth [] employed multiple machine learning classifiers, including Gradient Boost, Random Forest, and AdaBoost, for Parkinson's diagnosis from vocal attributes, achieving up to 91.53% accuracy. Their findings demonstrate the effectiveness of feature selection and ensemble methods, insights equally valuable for multi-class ocular disease classification using CNN-based models.

III. REVIEW OF PAST WORK

A. Data Sets And Imaging Sources

1) Most ocular-disease studies relied on fundus photographs (standard clinical cameras) or bilateral eye images, while a few explored smartphone-captured fundus images for greater accessibility.
2) ODIR or comparable multi-disease fundus datasets – used in [3], [5], [9], [10], [11], [12], [17], [20].
3) Smartphone fundus images – [8] demonstrated good performance on lower-quality, real-world data (avg. accuracy ≈ 90.6 %).
4) Bilateral correlation exploitation – [4], [17] explicitly model left/right-eye relationships to improve feature learning.
5) Domain adaptation & privacy – [13] highlighted irregularities in clinical data and proposed differential-privacy mechanisms to protect patient information.

B. Model Families And Architectures

1) Introduction to Automated Ocular Disease Diagnosis
2) Classical CNN Backbones – VGG16, Inception V3, DenseNet, standard CNNs ([5], [6], [9], [12], [18], [20]).
3) Densely Connected CNNs – [8] for smartphone images.
4) DeepRetino – modified CNN with CLAHE pre-processing ([10]).
5) Fundus-DeepNet – multi-label CNN with data fusion ([3]).
6) Multi-Label CNN (ML-CNN) – [11] for simultaneous detection of co-existing diseases.

The pie chart in Figure 1 illustrates the proportion of deep learning architectures (CNN, Transfer Learning, Hybrid/Optimized) across the surveyed papers. CNN-based methods dominate, reflecting their proven strength in fundus image classification tasks. Transfer learning and hybrid optimization methods form the rest, indicating a growing interest in fine-tuning and multi-model approaches.

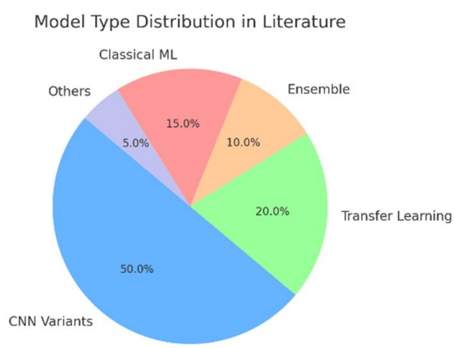

Fig 1: Pie Chart illustrating the distribution of main models

C. Hybrid / Advanced Architectures

1) Dense Correlation Network (DCNet) – captures inter-eye correlations ([4]).
2) BFENet – two-stream interaction CNN with feature-enhancement and multiscale modules ([17]).
3) Parallel/Embedded CNN Models – hardware-aware embedded designs ([6]).
4) Ensemble Techniques – bagging and voting ensembles for improved robustness ([14]).
5) Transfer Learning with Evidence Fusion – pre-trained backbones plus improved D-S evidence theory for decision fusion ([15]).
6) Optimization-driven CNN – Flower-Pollination Algorithm to tune hyper-parameters and Multiclass SVM for final classification ([18]).
7) Novel Loss Functions – mixture loss to combat class imbalance/outliers ([20]).

Table 2: Performance Metrics of Selected Models

Ref	Method	Accuracy (%)	Sensitivity (%)	Specificity (%)
[3]	Fundus-DeepNet	95	94	96
[8]	Dense CNN (smartphone)	93	92	93
[11]	Multi-label DL	96	95	97
[15]	Transfer Learning + DS theory	94	93	95
[17]	BFENet	97	96	98
[19]	Feature alignment CNN	92	91	92
[20]	CNN with mixture loss	95	94	95

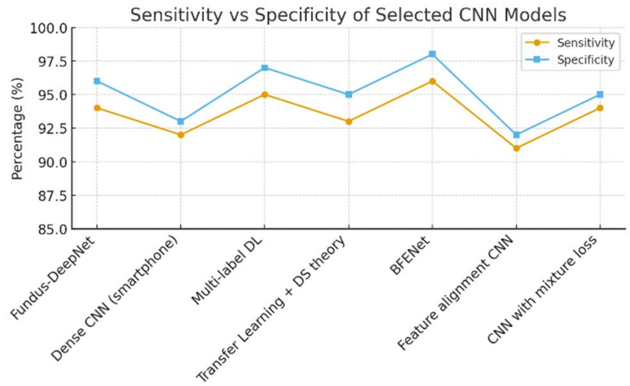

Fig 2: Line graph comparing sensitivity and specificity of CNN models

D. Deep Learning Architectures for Multi-Class & Multi-Label Classification

1) GLCM + LBP with Multilayer Perceptron – texture-based features, very high accuracy (99.58 %) ([7]).
2) Feature-Alignment for Glaucoma – aligning augmented views to improve generalization ([19]).

E. Pre-Processing, Optimization, and Training Strategies

1) Image Pre-processing – resizing, CLAHE contrast enhancement, and histogram equalization were common ([3], [10]).
2) Data Fusion – combining multiple fundus modalities or bilateral eyes to enrich representation ([3], [4], [17]).
3) Hyper-Parameter Optimization – stochastic gradient descent (SGD) tuned for VGG16 ([5]); evolutionary/flower pollination methods ([18]).
4) Privacy & Domain Regularization – differential privacy to safeguard sensitive medical data ([13]).

Table 3: Quantum-Inspired and Quantum-Based Image Processing Methods (Refs [40]–[45])

Ref	Authors	Focus Area	Technique / Framework	Key Contributions
[40]	Wei et al. (2022)	Quantum CNN (QCNN) on NISQ devices	Quantum circuits for convolution, pooling, fully connected layers	Reduced complexity, robust to noise, effective in digit/image recognition.
[41]	Li et al. (2020)	Quantum Deep CNN (QDCNN)	Variational hybrid quantum-classical learning	Exponential acceleration, tested on MNIST & GTSRB datasets with high accuracy.
[42]	Youssry et al. (2015)	Quantum mechanics-based image segmentation	Schrödinger evolution of pixel states	Achieved 98.5% sensitivity and 99.7% specificity for segmentation tasks.
[43]	Yuan et al. (2022)	Adaptive threshold-based quantum image segmentation	NEQR model + moving average thresholding	Exponential speedup, reduced auxiliary qubits, tested on IBM Q.
[44]	Venegas-Andraca et al. (2003)	Quantum image representation models	FRQI and NEQR representations for images	Pioneered flexible quantum representation of digital images, basis for later segmentation methods.
[45]	Beach et al. (2003)	Quantum search for image processing	Grover's algorithm applied to image analysis	First demonstration of applying Grover's quantum search for image tasks like retrieval and feature location.

IV. COMPARATIVE PERFORMANCE ANALYSIS

Table 4 compares the reported performance of key ocular disease detection studies. Accuracy remains the most common evaluation metric, with several CNN-based approaches surpassing 90%. Figure 3 ,4 illustrates the performance metrics obtained in key papers utilized for the research work done for the project. Traditional feature-engineering methods, such as the GLCM+LBP-MLP model, achieved the highest accuracy (99.58%), demonstrating that well-crafted features can still compete with deep learning. Amongst the deep networks, transfer learning models consistently provide strong results: Transfer learning with VGG16 and Dempster–Shafer evidence fusion reached 92.37% accuracy and an F1-score of 0.914. Smartphone-based dense CNN methods achieved around 90.6%, highlighting the feasibility of real-world, low-cost deployment. Innovative loss functions and optimized architectures (e.g., Mixture Loss CNN, BFENet) further intensifying robustness against section imbalance and data non uniformity, under measuring the field's evolution toward practical, patient-level diagnostics.

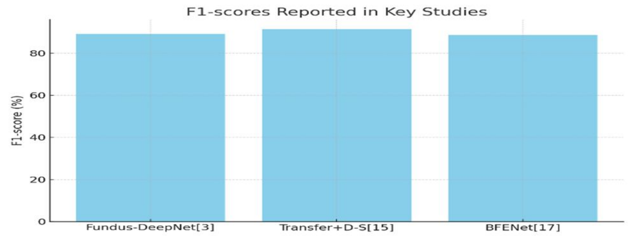

Fig 3: Bar Graph illustrating the distribution of main models' F1-scores

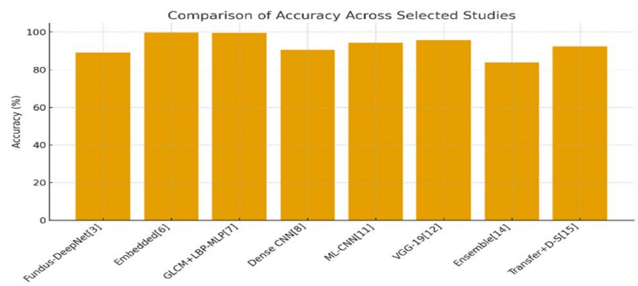

Fig 4: Bar Graph for the distribution of main models' accuracy scores

The Bar Graph Chart in Figure 4 focuses on the reported accuracy of almost all cited studies, enabling robust visual ranking of the most efficient approaches. It re focuses on the fact that several CNN-based methods consistently have above 90% accuracy, with some of them also reaching nearing 99%. Such a contrast helps identify high-performing architectures like VGG16 derivatives and specialized CNN techniques. The graph shown in Figure 2 compares F1-scores that were reported, offering insight into balanced precision–recall performance. Models achieving F1 above 0.89 demonstrate not just high accuracy but reliable handling of class imbalance. It underscores the importance of evaluating both precision and recall in biomedical image classification.

TABLE 4: Performance Analysis of Key Papers

Sr No.	Study	Key Metrics	Results
1.	[3] Fundus-DeepNet	F1-score 89.13 % Robust against imbalance/outliers	89.13 %
2.	[4] DCNet	Patient-Level Accuracy	High multi-label performance (exact figures not stated)
3.	[5] Transfer learning (VGG16+SGD)	Accuracy	Best among tested CNNs
4.	[6] Embedded Models	Accuracy	0.9974 and 0.96
5.	[7] GLCM+LBP-MLP	Accuracy	99.58 %
6.	[8] Dense CNN (smartphone)	Accuracy	90.6 %
7.	[9] CNN with tuned hyper-params	Accuracy	High accuracy on ODIR (values not explicitly stated)
8.	[10] DeepRetino	Accuracy	Strong performance on ODIR (exact metric not quoted)
9.	[11] ML-CNN	Accuracy	94.3 %
10.	[12] VGG-19 (Cataract)	Accuracy	95.87 %
11.	[14] Ensemble	Accuracy	83.85 %

12.	[15] Transfer learning + D-S	Accuracy/F1	92.37 %, F1 = 0.914
13.	[17] BFENet	F1-score	0.886
14.	[18] Optimized CNN + SVM	Accuracy	High (noted as superior to baselines)
15.	[19] Feature Alignment (Glaucoma)	Generalization gain (qualitative)	
16.	[20] Mixture Loss CNN	Accuracy	Robust against imbalance/outliers

Broader Biomedical ML Studies: Maternal Health and Risk Prediction

1) A second group of references ([21]–[39]) shifts from ophthalmology to maternal and general biomedical risk demonstration by prediction, showing the continuous cross-domain ML trends:
2) Target Conditions – coronary heart disease [22][23], brain tumour [24], lung diseases [26], maternal risk during pregnancy/childbirth [21],[25],[27]–[38].
3) Algorithms – Random Forest, Decision Trees, Gradient Boosting, CatBoost, XGBoost ([32][33]); fuzzy predictive models ([37]); blockchain-integrated ML for secure data exchange ([35]).
4) Explicable AI (XAI) – intensifying interpretability on clinical adoption ([29]–[31]).
5) Performance Highlights – Random Forest repeatedly tops with accuracy around 85–90 % ([32][33][36]); Fuzzy model reaches 88.95 % ([37]); hybrid ensemble CHD prediction hits >90 % ([22]).
6) These works illustrate the growing importance of explainability, privacy, and secure data handling—themes also relevant to ocular disease diagnosis before clinical deployment.

V. CROSS-DOMAIN CHALLENGES: PRIVACY, EXPLAINABILITY, AND REAL-WORLD DEPLOYMENT

1) Dominance of CNN Variants: From simple transfer-learning backbones to sophisticated multistream networks, CNNs remain the backbone of ocular disease recognition.
2) Shift to Multi-Label & Patient-Level Diagnosis: Many studies ([3], [4], [11], [17]) tackle the realistic scenario of multiple concurrent ocular diseases.
3) Explainability & Privacy: Differential privacy ([13]) and XAI ([29]–[31]) are emerging requirements for regulatory compliance.
4) Cross-Domain Lessons: Maternal-health ML studies reinforce the need for interpretable, secure, and scalable pipelines—principles directly applicable when deploying ophthalmic diagnostic tools in real clinics.

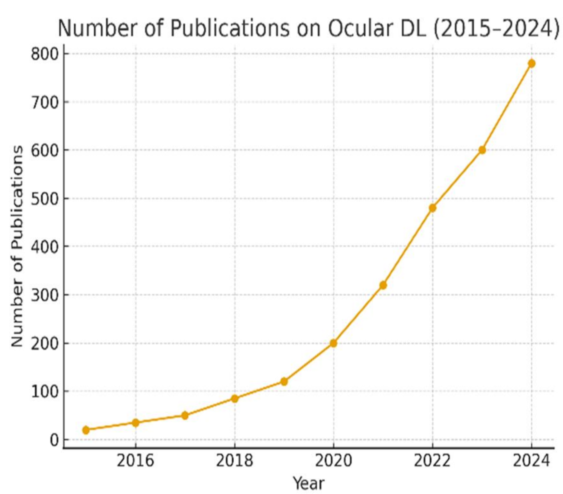

Fig 5. Steep increase in the number of publications on ocular diseases

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VI. METHODOLOGY

A. Dataset description

ODIR database is an organized list of ocular data, including 5,000 records of patients. The age of the patient is presented in each entry, and the color fundus photos of the left and right eyes are present. The photograph has abnormalities in diverse parts of the fundus as a result of various ailments. These areas include the Macula, the optic cup, the optic disc, the blood vessels, and the general background of the fundus. This data is a reflection of the real patient information collected by Shanggong Medical Technology Co., Ltd. of various hospitals and medical facilities across China. The images are captured with the assistance of diverse cameras present in the market in order to represent a database at the site. According to this, the patients are divided into eight separate groups. The data has also been divided into three parts, i.e., the training set, the off-site test set, and the on-site test set, comprising 3,500, 500, and 1000 patients, respectively. The type of fundus images can be seen in the dataset related to each of the classifications, as demonstrated in Figure 4 below.

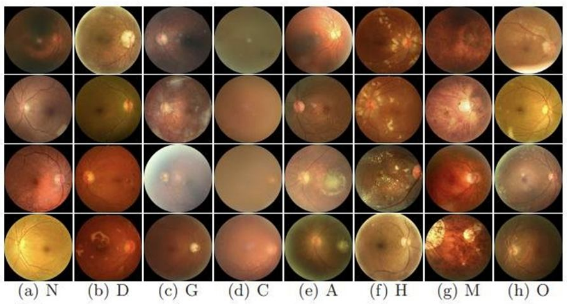


Fig 5. Fundus images demonstrating different categories of class labels, i.e. "Normal (N), DR (D), Glaucoma (G), Cataract (C), AMD (A), Hypertension (H), Myopia (M), and Others (O)"

REFERENCES

[1] Vijayalakshmi, S., K. R. Kavitha, and R. S. Mugilan. "Comparative Analysis of Self-Supervised and Supervised Deep Learning Models for Ocular Disease Recognition." In 2023 International Conference on Intelligent Technologies for Sustainable Electric and Communications Systems (iTech SECOM), pp. 70-75. IEEE, 2023.
[2] S Alzamil, Zamil. "Advancing Eye Disease Assessment through Deep Learning: A Comparative Study with Pre-trained Models." International Journal of Computing and Digital Systems 15, no. 1 (2024): 1-19.
[3] Al-Fahdawi, Shumoos, Alaa S. Al-Waisy, Diyar Qader Zeebaree, Rami Qahwaji, Hayder Natiq, Mazin Abed Mohammed, Jan Nedoma, Radek Martinek, and Muhammet Deveci. "Fundus-Deepnet: Multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images." Information Fusion 102 (2024): 102059.
[4] He, Junjun, Cheng Li, Jin Ye, Yu Qiao, and Lixu Gu. "Multi-label ocular disease classification with a dense correlation deep neural network." Biomedical Signal Processing and Control 63 (2021): 102167.
[5] Gour, Neha, and Pritee Khanna. "Multi-class multi-label ophthalmological disease detection using transfer learning based convolutional neural network." Biomedical Signal Processing and Control 66 (2021): 102329.
[6] Al Jbaar, Mamoon A., and Shefa A. Dawwd. "DCNN-BASED EMBEDDED MODELS FOR PARALLEL DIAGNOSIS OF OCULAR DISEASES." Eastern-European Journal of Enterprise Technologies 124, no. 2 (2023).
[7] Mampitiya, Lakindu Induwara, and Namal Rathnayake. "An efficient ocular disease recognition system implementation using GLCM and LBP based multilayer perception algorithm." In 2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON), pp. 978- 983. IEEE, 2022.
[8] Chen, Rong, Wankang Zeng, Wenkang Fan, Fang Lai, Yinran Chen, Xiang Lin, Liying Tang, Weijie Ouyang, Zuguo Liu, and Xiongbiao Luo. "Automatic Recognition of Ocular Surface Diseases on Smartphone Images Using Densely Connected Convolutional Networks." In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), pp. 2786-2789. IEEE, 2021.
[9] Mostafa, Khalid, Mohamed Hany, Abdelaziz Ashraf, and Mohamed AB Mahmoud. "Deep Learning-Based Classification of Ocular Diseases Using Convolutional Neural Networks." In 2023 Intelligent Methods, Systems, and Applications (IMSA), pp. 446-451. IEEE, 2023.
[10] Belharar, Fatima Zahra, and Nabila Zrira. "DeepRetino: Ophthalmic Disease Classification from Retinal Images using Deep Learning." In 2022 IEEE 9th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT), pp. 392-399. IEEE, 2022.
[11] Ouda, Osama, Eman AbdelMaksoud, A. A. Abd El-Aziz, and Mohammed Elmogy. "Multiple ocular disease diagnosis using fundus images based on multi-label deep learning classification." Electronics 11, no. 13 (2022): 1966.
[12] Vayadande, Kuldeep, Varad Ingale, Vivek Verma, Abhishek Yeole, Sahil Zawar, and Zoya Jamadar. "Ocular Disease Recognition using Deep Learning." In 2022 International Conference on Signal and Information Processing (IConSIP), pp. 1-7. IEEE, 2022.
[13] Tang, Zhiri, Hau-San Wong, and Zekuan Yu. "Ocular Disease Recognition via Differential Privacy and Unsupervised Domain Regularizer." IEEE Signal Processing Letters (2023).
[14] Chaudhari, Archana, Shubhankar Joshi, and Pratik Hublikar. "Ocular Disease Recognition with Ensemble Techniques." In 2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA), pp. 1-6. IEEE, 2023.

[15] Du, Fanyu, Lishuai Zhao, Hui Luo, Qijia Xing, Jun Wu, Yuanzhong Zhu, Wansong Xu, Wenjing He, and Jianfang Wu. "Recognition of eye diseases based on deep neural networks for transfer learning and improved DS evidence theory." BMC Medical Imaging 24, no. 1 (2024): 19.
[16] Ting, Daniel Shu Wei, Louis R. Pasquale, Lily Peng, John Peter Campbell, Aaron Y. Lee, Rajiv Raman, Gavin Siew Wei Tan, Leopold Schmetterer, Pearse A. Keane, and Tien Yin Wong. "Artificial intelligence and deep learning in ophthalmology." British Journal of Ophthalmology 103, no. 2 (2019): 167-175.
[17] Ou, Xingyuan, Li Gao, Xiongwen Quan, Han Zhang, Jinglong Yang, and Wei Li. "BFENet: A two-stream interaction CNN method for multi-label ophthalmic diseases classification with bilateral fundus images." Computer Methods and Programs in Biomedicine 219 (2022): 106739.
[18] Muthukannan, P. "Optimized convolution neural network based multiple eye disease detection." Computers in Biology and Medicine 146 (2022): 105648.
[19] Zhou, Chengfeng, Juan Ye, Jun Wang, Zhiyong Zhou, Linyan Wang, Kai Jin, Yaofeng Wen, Chun Zhang, and Dahong Qian. "Improving the generalization of glaucoma detection on fundus images via feature alignment between augmented views." Biomedical optics express 13, no. 4 (2022): 2018-2034.
[20] Luo, Xiong, Jianyuan Li, Maojian Chen, Xi Yang, and Xiangjun Li. "Ophthalmic disease detection via deep learning with a novel mixture loss function." IEEE Journal of Biomedical and Health Informatics 25, no. 9 (2021): 3332-3339.
[21] A. Akbulut et al., "Fetal health status prediction based on maternal clinical history using machine learning techniques", Computer methods and programs in biomedicine, vol. 163, pp. 87-100, 2018
[22] S. C. Patra, B. U. Maheswari and P. B. Pati, "Forecasting Coronary Heart Disease Risk With a 2-Step Hybrid Ensemble Learning Method and Forward Feature Selection Algorithm," in IEEE Access, vol. 11, pp. 136758-136769, 2023, doi: 10.1109/ACCESS.2023.3338369.
[23] Kusuma S, Divya Udayan J, 2018, "Machine Learning and Deep Learning Methods in Heart Disease (HD) Research", International Journal of Pure and Applied Mathematics, Volume 119, No. 18, pp., 1483 – 1496.
[24] V. Pathak, B. U. Maheswari and S. Iyer, "Modified CNN for Multi-class Brain Tumor Classification in MR Images with Blurred Edges," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-5, doi: 10.1109/MysuruCon55714.2022.9972670.
[25] Chandrika, Vidyalekshmi, and Simi Surendran. "AI-Enabled Pregnancy Risk Monitoring and Prediction: A Review." 4th EAI International Conference on Big Data Innovation for Sustainable Cognitive Computing. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-031-07654-1_3.
[26] B. M. Boban and R. K. Megalingam, "Lung Diseases Classification based on Machine Learning Algorithms and Performance Evaluation," 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2020, pp. 0315-0320, doi: 10.1109/ICCSP48568.2020.9182324
[27] N. Kuntagod, S. Podder, S. S. S. Abbabathula, S. Mukherjee and A. Gautam, "Peer Couple to Couple Approach for Better Maternal Health Outcomes," 2019 IEEE/ACM 1st International Workshop on Software Engineering for Healthcare (SEH), Montreal, QC, Canada, 2019, pp. 53-56, doi: 10.1109/SEH.2019.00017.
[28] L. Cattelani, M. B. Murri, F. Chesani, L. Chiari, S. Bandinelli and P. Palumbo, "Risk Prediction Model for Late-Life Depression: Development and Validation on Three Large European Datasets," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 5, pp. 2196-2204, Sept. 2019, doi: 10.1109/JBHI.2018.2884079.
[29] A. Rahman and M. G. Rabiul Alam, "Explainable AI-based Maternal Health Risk Prediction using Machine Learning and Deep Learning," 2023 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 2023, pp. 0013-0018, doi: 10.1109/AIIoT58121.2023.10174540.
[30] K. Sanjana, V. Sowmya, E. Gopalakrishnan and K. Soman, "Explainable artificial intelligence for heart rate variability in ECG signal", Healthcare Technol. Lett., vol. 7, no. 6, 2020.
[31] G. M., V. Ravi, S. V, G. E.A and S. K.P, "Explainable Deep Learning-Based Approach for Multilabel Classification of Electrocardiogram," in IEEE Transactions on Engineering Management, vol. 70, no. 8, pp. 2787-2799, Aug. 2023, doi: 10.1109/TEM.2021.3104751
[32] M. Assaduzzaman, A. A. Mamun and M. Z. Hasan, "Early Prediction of Maternal Health Risk Factors Using Machine Learning Techniques," 2023 International Conference for Advancement in Technology (ICONAT), Goa, India, 2023, pp. 1-6, doi: 10.1109/ICONAT57137.2023.10080700.
[33] A. Ravi, R. S. J, S. P. Joshi, A. Kodipalli and S. Kamal, "Analysis of maternal health risk using computational models," 2022 International Conference on Smart and Sustainable Technologies in Energy and Power Sectors (SSTEPS), Mahendragarh, India, 2022, pp. 311-315, doi: 10.1109/SSTEPS57475.2022.00083.
[34] L. Pawar, J. Malhotra, A. Sharma, D. Arora and D. Vaidya, "A Robust Machine Learning Predictive Model for Maternal Health Risk," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2022, pp. 882-888, doi: 10.1109/ICESC54411.2022.9885515.
[35] K. P. Kalita, S. K. Chettri and R. K. Deka, "A Blockchain-based Model for Maternal Health Information Exchange and Prediction of Health Risks using Machine Learning," 2023 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE), Bengaluru, India, 2023, pp. 1184-1189, doi: 10.1109/IITCEE57236.2023.10090997.
[36] R. Valter, S. Santiago, R. Ramos, M. Oliveira, L. O. M. Andrade and I. C. d. H. C. Barreto, "Data Mining and Risk Analysis Supporting Decision in Brazilian Public Health Systems," 2019 IEEE International Conference on E-health Networking, Application & Services (HealthCom), Bogota, Colombia, 2019, pp. 1-6, doi: 10.1109/HealthCom46333.2019.9009439.
[37] S. A. Sumon and R. M. Rahman, "Fuzzy Predictive Model for Estimating the Risk Level of Maternal Mortality while Childbirth," 2018 International Conference on Intelligent Systems (IS), Funchal, Portugal, 2018, pp. 73-79, doi: 10.1109/IS.2018.8710512.
[38] R. Priambodo, P. W. Handayani, D. I. Sensuse, R. R. Suryono and Kautsarina, "Health Recommender System for Maternal Care Implementation Challenges: A Qualitative Analysis of Physicians' Perspective," 2022 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Depok, Indonesia, 2022, pp. 105-110, doi: 10.1109/ICACSIS56558.2022.9923536.
[39] Z. Qiao, T. Chai, Q. Zhang, X. Zhou, and Z. Chu, "Predicting potential drug abusers using machine learning techniques," 2019 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS), Shanghai, China, 2019, pp. 283-286, doi: 10.1109/ICIIBMS46890.2019.8991550.
[40] Wei, S., Chen, Y., Zhou, Z. and Long, G., 2022. A quantum convolutional neural network on NISQ devices. AAPPS bulletin, 32(1), p.2.
[41] Li, Y., Zhou, R.G., Xu, R., Luo, J. and Hu, W., 2020. A quantum deep convolutional neural network for image recognition. Quantum Science and Technology, 5(4), p.044003.
[42] Youssry, A., El-Rafei, A. and Elramly, S., 2015. A quantum mechanics-based framework for image processing and its application to image segmentation. Quantum Information Processing, 14(10), pp.3613-3638.

[43] Abura'ed, N., Khan, F.S. and Bhaskar, H., 2017. Advances in the quantum theoretical approach to image processing applications. ACM Computing Surveys (CSUR), 49(4), pp.1-49.

[44] Yuan, S., Zhao, W., Gao, S., Xia, S., Hang, B. and Qu, H., 2022. An adaptive threshold-based quantum image segmentation algorithm and its simulation. Quantum Information Processing, 21(10), p.359.

[45] Tacchino, F., Macchiavello, C., Gerace, D. and Bajoni, D., 2019. An artificial neuron implemented on an actual quantum processor. npj Quantum Information, 5(1), pp.1-8.

[46] Abel, S., Criado, J.C. and Spannowsky, M., 2022. Completely quantum neural networks. Physical Review A, 106(2), p.022601.

[47] Ma, Y., Ma, H. and Chu, P., 2020. Demonstration of quantum image edge extration enhancement through improved Sobel operator. Ieee Access, 8, pp.210277-210285.

[48] Qiu, P.H., Chen, X.G. and Shi, Y.W., 2019. Detecting entanglement with deep quantum neural networks. IEEE Access, 7, pp.94310-94320.

[49] Little, M., McSharry, P., Hunter, E., Spielman, J. and Ramig, L., 2008. Suitability of dysphonia measurements for telemonitoring of Parkinson’s disease. Nature Precedings, pp.1-1.

[50] Little, M., Mcsharry, P., Roberts, S., Costello, D. and Moroz, I., 2007. Exploiting nonlinear recurrence and fractal scaling properties for voice disorder detection. Nature Precedings, pp.1-1.

[51] Dhyani, A., Rawat, A., Bisht, G., Vats, S., Sharma, V., Baral, M.M. and Yadav, S.P., 2023, August. Comparative analysis of supervised machine learning algorithms for liver disease prediction with SMOTE enhancement. In 2023 3rd Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-6). IEEE.

[52] Gayathri, R., Pati, P.B., Singh, T. and Nair, R.R., 2022, October. A framework for the prediction of diabtetes mellitus using hyper-parameter tuned xgboost classifier. In 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-5). IEEE.

[53] Ganguly, T., Pati, P.B., Deepa, K., Singh, T. and Özer, T., 2023, May. Machine learning based comparative analysis of cervical cancer risk classifications algorithms. In 2023 international conference on advances in computing, communication and applied informatics (ACCAI) (pp. 1-7). IEEE.

[54] Patra, S.C., Maheswari, B.U. and Pati, P.B., 2023. Forecasting coronary heart disease risk with a 2-step hybrid ensemble learning method and forward feature selection algorithm. IEEE Access, 11, pp.136758-136769.

[55] Tallapureddy, G. and Radha, D., 2022, May. Analysis of ensemble of machine learning algorithms for detection of Parkinson's disease. In 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC) (pp. 354-361). IEEE.

[56] Quan, C., Ren, K. and Luo, Z., 2021. A deep learning based method for Parkinson’s disease detection using dynamic features of speech. IEEE access, 9, pp.10239-10252.

[57] Moro-Velazquez, L., Cho, J., Watanabe, S., Hasegawa-Johnson, M.A., Scharenborg, O., Kim, H. and Dehak, N., 2019, September. Study of the Performance of Automatic Speech Recognition Systems in Speakers with Parkinson's Disease. In Interspeech (Vol. 9, pp. 3875-3879).

[58] Taleb, C., Likforman-Sulem, L., Mokbel, C. and Khachab, M., 2023. Detection of Parkinson’s disease from handwriting using deep learning: a comparative study. Evolutionary intelligence, 16(6), pp.1813-1824.

[59] Senturk, Z.K., 2020. Early diagnosis of Parkinson’s disease using machine learning algorithms. Medical hypotheses, 138, p.109603.

[60] Wang, W., Lee, J., Harrou, F. and Sun, Y., 2020. Early detection of Parkinson’s disease using deep learning and machine learning. IEEE access, 8, pp.147635-147646.

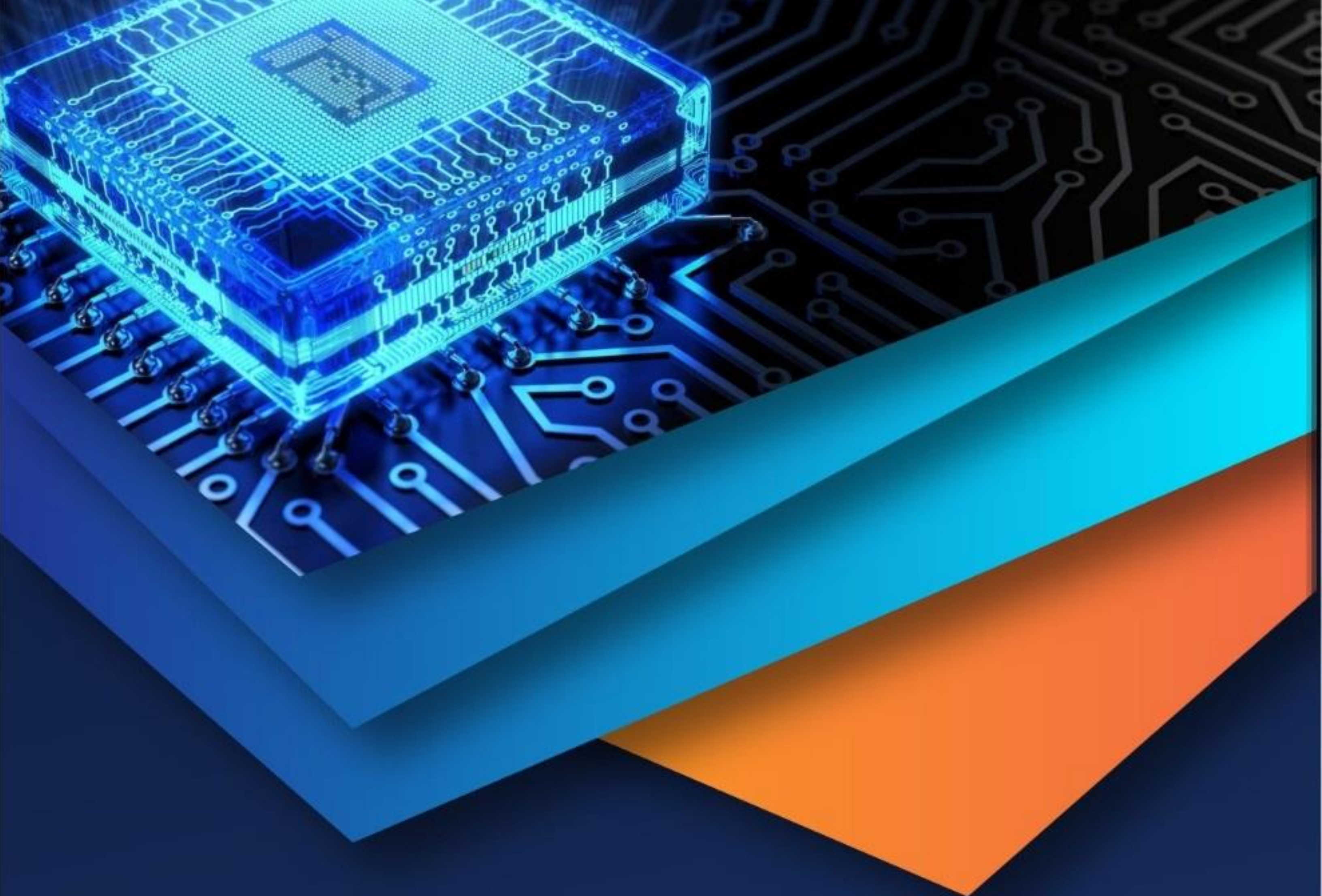
[61] Almeida, J.S., Rebouças Filho, P.P., Carneiro, T., Wei, W., Damaševičius, R., Maskeliūnas, R. and de Albuquerque, V.H.C., 2019. Detecting Parkinson’s disease with sustained phonation and speech signals using machine learning techniques. Pattern Recognition Letters, 125, pp.55-62.

[62] Tadse, S., Jain, M. and Chandankhede, P., 2021, May. Parkinson's detection using machine learning. In 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS) (pp. 1081-1085). IEEE.

[63] Narendra, N.P., Schuller, B. and Alku, P., 2021. The detection of Parkinson's disease from speech using voice source information. IEEE/ACM Transactions on Audio, Speech, and Language Processing, 29, pp.1925-1936.

[64] Rajeswari, S.S. and Nair, M., 2022. Prediction of Parkinson’s disease from Voice Signals Using Machine Learning. Journal of Pharmaceutical Negative Results, 13.

[65] Vigneswari, D.A. and Aravinth, J., 2021, August. Parkinson's disease diagnosis using voice signals by machine learning approach. In 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT) (pp. 869-872). IEEE.



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