**Internet of things and deep learning enabled diabetic retinopathy diagnosis using retinal fundus images**

**ABSTRACT**

There are several deep learning techniques that are used to perform the predictive analytics over big data in various medical tasks. Predictive analytics in medical healthcare is a challenging task yet ultimately helping the practitioners handle big data-informed timely decisions about patient’s medical health and treatment. This paper discusses the predictive analytics in healthcare. Patient’s medical record is obtained for experimental research. The two architectures of deep learning are implemented. Performance and accuracy of these applied algorithms are implemented and compared. Different deep learning techniques used in this research that reveals which algorithm is best suited for the prediction of diabetes over the patient. This project aims to help doctors and practitioners in early stage to predict diabetic retinopathy using deep learning techniques.

**INTRODUCTION**

Healthcare industry is a very large and sensitive meta data and must be carefully handled. One of the growing extremely fatal diseases all over the world is Diabetes Mellitus. Medical professionals require a reliable prediction system to diagnose this disease. Some of the useful deep learning techniques for examining the data from diverse perspectives and synopsizing it into valuable information. The accessibility and availability of huge amounts of data are able to provide us useful knowledge unless certain data mining techniques are applied to it. The main goal to this is to determine new patterns and interpret these patterns to deliver acute significant and useful information for the process. Diabetes may leads to heart disease, kidney disease, nerve damage, and blindness. Diabetes data mining in an efficient way for a crucial concerns. The data mining techniques and its way be discovered to create the appropriate approaches and techniques for an efficient classification of Diabetes dataset and in extracting it data patterns. In this study, medical bioinformatics analyses is done in diabetes prediction. The WEKA software is employed as a mining tool in diabetics diagnosis. The Pima Indian diabetes Data base was acquired from UCI repository that used for future analysis. The dataset was researched and analyzed to build an effective model that used to predict and diagnoses diabetes disease. Diabetic Retinopathy may be a complication of diabetes that's caused thanks to the changes within the blood vessels of the retina and is one among the leading causes of blindness in the developed world. Up to this , Diabetic Retinopathy remains screened manually by ophthalmologist which may be a time consuming process and hence this paper aims at automatic diagnosis of the disease into its different stages using deep learning. In our approach, we trained a Deep Convolutional Neural Network model on an outsized dataset consisting of around 35,000 images to automatically diagnose and thereby classify high resolution fundus images of the retina into five stages supported their severity. Within this paper, an application system is made which takes the input parameters because the patient’s details along side the fundus image of the attention . A trained deep Convolutional neural network model will further extract the features of the fundus images and later with the assistance of the activation functions like Relu and softmax along with optimizing techniques like Adam an output is obtained. The output obtained from the Convolutional Neural Network (CNN) model and therefore the patient details will collectively make a uniform report. In this study, we aim to apply the bootstrapping resembling technique to enhance the accuracy and then applying ResNet, CNN and compare their performance. The idea of Machine learning is to predict the longer term from past data. Machine learning focuses on the event of Computer Programs which will change when exposed to new data and therefore the basics of Machine Learning, implementation of an easy machine learning algorithm using python. It feed the training data to an algorithm, and therefore the algorithm uses thistraining data to offer predictions on a replacement test data.

Machine learning are often roughly separated in to three categories. Supervised learning program is given to both the input file and therefore the corresponding labelling to find out the info that has got to be labelled by a person's being beforehand. Unsupervised learning has no labels. It is directly fed to the learning algorithm. This algorithm has got to discover the clustering of the input file. Finally, Reinforcement learning dynamically interacts with its environment and it receives positive or feedback to enhance its performance. Deep learning is a part of machine learning in artificial intelligence that has networks able to adapt in learning unsupervised data that are unlabeled or unstructured . This proess is otherwise known as deep neural learning or deep neural networks. The Deep Learning consists of an algorithm called Convolutional Neural Network(ConvNet/CNN) which gets the input image, assign importance (learnable weights and biases) to various aspects/objects in that image and be able to distinguish one from the other. The pre-processing required in a ConvNet is much lesser as compared to the other classification algorithms. In Deep Learning primitive methods filters are hand-engineered that comes with enough training, Convolutional Networks have the ability to learn these filters/characteristics.

Diabetic retinopathy is a medical complication that is caused by the damage to the blood vessels of the light-sensitive tissue which is present at the back of the eye, retina, which can gradually lead to complete blindness and various other eye problems depending on the severity of Diabetic Retinopathy. It is observed that 40% − 45% of diabetic patients are likely to have DR in their life, but due to lack of knowledge and delayed diagnosis, the condition escalates quickly. Diabetes was once thought of as a disease of the affluent but it's now reached epidemic proportion in both developed and developing countries. Currently, a minimum of 366 million people worldwide has diabetes, and this number is probably going to extend as a results of an aging global population Globally, the quantity of individuals with DR will grow from 126.6 million in 2010 to 191.0 million by 2030, and that we estimate that the quantity with vision-threatening diabetic retinopathy (VTDR) will increase from 37.3 million to 56.3 million, if prompt action isn't taken. Diabetes is the best disease to apply deep learning principles to. There are numerous specialists chipping away at forecast of diabetes sickness and intricacies emerging from diabetes. There are many applications available which help the practitioners to study the disease and complications but many applications have their own advantages and flaws. According, Indian peoples are more prone to diabetes because of lots of reasons including lifestyle, consumption of type of food and inadequate physical activities. Diabetic Retinopathy is one of the major complications that affects the human eye of diabetic people. Damage to the blood vessels of light-sensitive tissue of the retina causes this disease. Diabetic Retinopathy (DR) is a compilation of diabetes that causes the blood vessel of the retina to swell and leak fluids and blood. It is the leading cause of blindness for people aged 20 to 64 years. Diabetic Retinopathy (DR) is the most common cause of visual loss in people across the world.. According to the article presented in the claims that approximately one-third of the 285 million population having diabetes mellitus worldwide intimates signs of diabetic retinopathy.

**EXISTING SYSTEM**

Apart from a binocular model for the various classes of Diabetic Retinopathy detection task is also trained and evaluated to further prove the effectiveness of the binocular design. The final result shows that, on a 10% validation set, the binocular model achieves a kappa score of 0.829 which is higher than that of existing non ensemble model. In the end the analogy between confusion matrices obtained through models with paired and unpaired inputs is performed and it demonstrates that the binocular architecture does improve the classification performance.

**PROBLEM STATEMENTS**

The problem addressed in this study is the need for a cost-effective and scalable solution for the detection of diabetic retinopathy (DR), a leading cause of blindness in adults with diabetes. Current methods for DR detection are time-consuming, expensive, and require specialized equipment and trained personnel, making them inaccessible in many regions. The objective of this study is to develop and evaluate a deep learning model for automated DR detection from retinal images, which can improve the accessibility and affordability of DR screening and diagnosis.

**MOTIVATION**

The motivation behind developing a deep learning model for diabetic retinopathy detection is the significant burden of this disease on patients, healthcare systems, and society. Early detection and treatment of DR are critical to preventing blindness and improving patient outcomes. However, current methods for DR detection are expensive and inaccessible in many regions, leading to delays in diagnosis and treatment. By developing a cost-effective and scalable solution for DR detection using deep learning, this study aims to improve the accessibility and affordability of DR screening and diagnosis, ultimately improving patient outcomes and reducing the burden on healthcare systems**.**

**Scope**

The scope of this study is to develop and evaluate a deep learning model for automated diabetic retinopathy (DR) detection from retinal images. The study will use publicly available retinal image datasets with labeled DR severity to train and validate the deep learning model. The deep learning model will use a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for feature extraction, sequence modeling, and classification of DR severity. The performance of the deep learning model will be compared with other state-of-the-art DR detection methods to assess its superiority and effectiveness. The developed deep learning model can have significant clinical implications, including early detection and treatment of DR, reducing the workload of ophthalmologists, and improving patient outcomes. However, the study may face limitations such as limited sample size and biased data, which can affect the generalizability of the deep learning model. The scope of this study is limited to the development and evaluation of a deep learning model for automated DR detection and does not include implementation and validation in real-world clinical settings.

**OBJECTIVES**

**The objectives of this study are:**

1. To develop a deep learning model for automated diabetic retinopathy (DR) detection from retinal images.

2. To evaluate the performance of the deep learning model using standard techniques, such as backpropagation and gradient descent, and performance metrics such as accuracy, sensitivity, and specificity.

3. To compare the performance of the deep learning model with other state-of-the-art DR detection methods to assess its superiority and effectiveness.

4. To assess the clinical implications of the developed deep learning model, including early detection and treatment of DR, reducing the workload of ophthalmologists, and improving patient outcomes.

5. To identify any limitations or challenges faced in the development and evaluation of the deep learning model, such as limited sample size or biased data, that may affect the generalizability of the model.

6. To provide recommendations for future research in the field of DR detection using deep learning, such as the implementation and validation of the model in real-world clinical settings.

**PROPOSED SYSTEM**

The proposed system in this study is a deep learning model for automated diabetic retinopathy (DR) detection from retinal images. The model will use a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for feature extraction, sequence modeling, and classification of DR severity. The deep learning model will be trained and validated using publicly available retinal image datasets with labeled DR severity. The performance of the model will be evaluated using standard techniques, such as backpropagation and gradient descent, and performance metrics such as accuracy, sensitivity, and specificity. The proposed system aims to provide a cost-effective and scalable solution for DR detection that can improve the accessibility and affordability of DR screening and diagnosis. The clinical implications of the proposed system include early detection and treatment of DR, reducing the workload of ophthalmologists, and improving patient outcomes. The limitations and challenges of the proposed system, such as limited sample size and biased data, will also be assessed in the study.

**Advantages**

1. Precision: Deep learning models offer high precision in detecting diabetic retinopathy.

2. Efficiency: The use of deep learning algorithms can speed up the process of screening for diabetic retinopathy.

3. Cost-effectiveness: Automated diabetic retinopathy detection using deep learning is a cost-effective alternative to traditional screening methods.

4. Scalability: Deep learning models can be easily scaled to analyze large datasets and accommodate additional retinal diseases and conditions.

5. Accessibility: Automated diabetic retinopathy detection using deep learning can improve access to screening and diagnosis in underserved areas.

6. Sensitivity: Deep learning models have high sensitivity in detecting early signs of diabetic retinopathy.

7. Workload reduction: The use of deep learning for diabetic retinopathy detection can reduce the workload of ophthalmologists and healthcare professionals.

8. Objectivity: Deep learning algorithms offer an objective and consistent method for diabetic retinopathy screening and diagnosis.

9. Early intervention: Early detection of diabetic retinopathy using deep learning can lead to earlier intervention and treatment.

10. Improved patient outcomes: The use of deep learning for diabetic retinopathy detection can lead to improved patient outcomes and quality of life.

**DISADVANTAGES**

1. Lack of transparency: Deep learning models can be complex and lack transparency, making it difficult to understand the decision-making process.

2. Dependence on data: Deep learning models rely heavily on large volumes of high-quality data, which may not always be available.

3. Overfitting: Deep learning models can overfit to training data, leading to poor generalization and performance on new data.

4. Hardware requirements: Deep learning models require significant computational power, making it difficult to deploy on low-end devices.

5. Vulnerability to adversarial attacks: Deep learning models can be vulnerable to adversarial attacks, where subtle changes to input data can lead to incorrect output.

6. Limited interpretability: Deep learning models may not provide meaningful insights into the underlying biological processes or mechanisms of diabetic retinopathy.

7. Ethical concerns: The use of deep learning for diabetic retinopathy detection raises ethical concerns around privacy, data ownership, and bias.

8. Maintenance and updates: Deep learning models require regular maintenance and updates to ensure optimal performance and accuracy.

9. Limited availability: The availability of deep learning models and expertise may be limited in some regions or healthcare systems.

10. Regulatory and legal considerations: The use of deep learning for diabetic retinopathy detection may be subject to regulatory and legal considerations, particularly around patient safety and liability.

**CHAPTER 2**

**LITERATURE SURVEY**

Many eye conditions, including trachoma, cataracts, and corneal ulcers, can impair vision. Only when these eye illnesses are effectively diagnosed at an early stage can progression be stopped. These eye illnesses have a wide range of visually discernible symptoms. To accurately diagnose eye illnesses, it is required to analyse a wide range of symptoms. A deep neural network model is used to discriminate between different diseases like diabetic retinopathy, glaucoma and cataract and high-resolution retina images taken under a variety of imaging settings. In terms of screening Eye Disease Identification using Deep Learning, it may prompt patients to contact an ophthalmologist. The created model has a lower level of complexity and we have developed a method for automatically classifying any retinal fundus image as healthy or sick using a deep learning model. Using existing datasets, image pre-processing methods, deep learning models, and performance evaluation criteria, we have developed a model for the automated identification of diabetic eye illness. It includes works that used built DL network architecture and used a combined DL and ML approach in terms of classification algorithms. From medical photos, we may deduce that CNN is now the most popular deep neural network, especially for the identification of diabetic eye illness and the diagnosis of other pathological indications. The effectiveness of different current models, including neural networks and deep learning algorithms, in detecting eye disease has been examined. The process of identifying eye diseases using retinal images is broken down into several smaller processes, including feature extraction, classification, and picture pre-processing. This study provides an overview of deep learning, its algorithms, the operation of convolution neural networks, and its applications to image processing, machine learning, and deep learning techniques that are utilized for retinal image-based eye disease identification.

**2.1 Multi-Expert Deep Networks for Multi-Disease Detection in Retinal Fundus Images**

Automatic diagnosis of eye diseases from retinal fundus images is quite challenging. Common public datasets include images of subjects with multiple diseases with uneven distribution of labels. Rare diseases are especially challenging due to their under-representation in such datasets. In this paper, we propose a training pipeline for the multi-labelled classification with uneven distribution of the sample size and sample difficulty. First, we guide the training of the initial model by weighing the training loss using an inverse-frequency for each class. This will balance the training on over-represented and under-represented samples. We then adjust the class weights using the aggregated loss for each class, and train for more iterations. In this way, the model at each iteration will focus more on difficult samples and cover the shortcomings of the previous model. Finally, we ensemble together all the models using out proposed Heuristic Stacking algorithm for improving multi-label predictions beyond simple averaging. Our experimental results on the Retinal Image Analysis for Multi-Disease Detection (RIADD)-2021 challenge dataset show that the proposed approach achieves a 88.24% accuracy score, which is competitive with the top three ranked methods of the competition. Furthermore, we perform ablation study to stress test our Heuristic Stacking ensemble methods versus classical methods such as bagging n multi-label classification problems [12].

**2.2 Generative Adversarial Networks (GANs) for Retinal Fundus Image Synthesis**

The lack of access to large, annotated datasets and legal concerns regarding patient privacy are limiting factors for many applications of deep learning in the retinal image analysis domain. Therefore, the idea of generating synthetic retinal images, indiscernible from real data, has gained more interest. Generative adversarial networks (GANs) have proven to be a valuable framework for producing synthetic databases of anatomically consistent retinal fundus images. In Ophthalmology, GANs in particular have shown increased interest. We discuss here the potential advantages and limitations that need to be addressed before GANs can be widely adopted for retinal imaging [5].

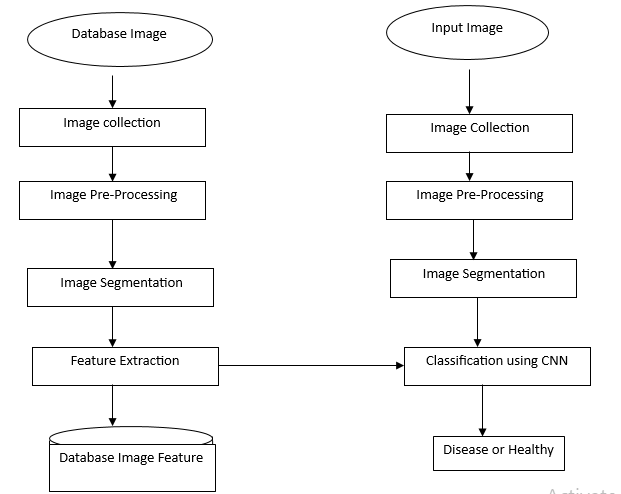
* 1. **Multi-Label Classification of Fundus Images With EfficientNet**

Convolutional neural network (CNN) has achieved remarkable success in the field of fundus images due to its powerful feature learning ability. Computer-aided diagnosis can obtain information with reference value for doctors in clinical diagnosis or screening through proper processing and analysis of fundus images. However, most of the previous studies have focused on the detection of a certain fundus disease, and the simultaneous diagnosis of multiple fundus diseases still faces great challenges. We propose a multi-label classification ensemble model of fundus images based on CNN to directly detect one or morefundus diseases in the retinal fundus images. Every single model consists of two parts. The first part is a feature extraction network based on EfficientNet, and the second part is a custom classification neural network for multi-label classification problems. Finally, the output probabilities of different models are fused as the final recognition result. And it was trained and tested on the data set provided by ODIR 2019 (Peking University International Competition on Ocular Disease Intelligent Recognition). The experimental results show that our model can be trained on fewer data sets and get good results [1].

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| **Sl.No** | **Authors** | **Year of publication** | **Title of the paper** | **Methodology** | **Limitations** |
| 1 | Jing Wang, Liu Yang, Zhanqiang Huo , Weifeng He, and Junwei Luo | 2020 | Multi-Label Classification of Fundus Images With EfficientNet. | The purpose of this study is to establish a framework for  automatic identification of multi-label fundus diseases, and  to achieve it by designing a corresponding ensemble model. | The amount  of data for some diseases is very limited, which makes it  very difficult to improve the performance of a network.  Another basic limitation comes from the black box of the  nature of deep networks. The network automatically learns  features from images, but the specific features learned are  unknown. |
| 2. | Balla Goutam  , Mohammad Farukh Hashmi  , (Senior Member, Ieee),  Zong Woo Geem , (Senior Member, Ieee), and Neeraj Dhanraj Bokde | 2022 | A Comprehensive Review of Deep Learning  Strategies in Retinal Disease Diagnosis  Using Fundus Images | The proposed review focuses mainly on providing an in depth review of various DL strategies recently implemented  for retinal disease diagnosis using fundus images. This study  also intends to outline possible future directions for new  researchers interested in AI-based retinal disease diagnosis. | The models  trained on IDRiD,  Messidor, DRIVE datasets may not perform well on other datasets. These may not be suitable for efficient model training, |
| 3. | Juan Carrillo  , Lola Bautista, Jorge Villamizar, Juan Rueda, Mary Sanchez and Daniela Rueda | 2019 | Glaucoma Detection Using Fundus Images of The Eye | This work presents a computational tool for automatic glaucoma detection from fundus images of the eye. This work propose a  novel method for cup segmentation, which shows an improvement  in the accuracy compared to other methods | The vessels segmentation requires an  improvement due to some fails in different images and residual  noise after the segmentation. |
| 4. | Ayesha Kazi, Prerna Sukhija, Miloy Ajmera, Kailas Devadkar | 2018 | Processing Retinal Images to Discover Diseases | This paper aims to not only accurately classify the disease  into one of the three possible abnormalities or assert that  it is a healthy retina. The image may fall into more than  one category. For example, a retina which shows any  presence of Diabetic Retinopathy could also show hints of  Glaucoma and/or Cataract | It cannot determine the presence of a variation in the image  (like highlighting, tessellation etc) preceding the  classification step, for training the neural network, and to  use unique combinations for different cases. |

**Table 2.1 Literature Survey**

**Methodology and Block Diagram**



**The System design mainly consists of**

1. Image Collection

2. Image Preprocessing

3. Image Segmentation

4. Feature Extraction

5. Training 6. Classification

1. **Image Collection**

The dataset that we have used in this project is available publicly on the internet

1. **Image Preprocessing**

The goal of pre-processing is an improvement of image data that reduces unwanted distortions and enhances some image features important for further image processing. Image pre-processing involves three main things a) Grayscale conversion b) Noise removal c) Image enhancement

**a)Grayscale conversion**: Grayscale image contains only brightness information. Each pixel value in a grayscale image corresponds to an amount or quantity of light. The brightness graduation can be differentiated in grayscale image. Grayscale image measures only light intensity 8 bit image will have brightness variation from 0 to 255 where ‘0’ represents black and ‘255’ represent white. In grayscale conversion color image is converted into grayscale image shows. Grayscale images are easier and faster to process than colored images. All image processing technique are applied on grayscale image.

**b) Noise Removal**: The objective of noise removal is to detect and remove unwanted noise from digital image. The difficulty is in deciding which features of an image are real and which are caused by noise. Noise is random variations in pixel values.

We are using median filter to remove unwanted noise. Median filter is nonlinear filter, it leaves edges invariant. Median filter is implemented by sliding window of odd length. Each sample value is sorted by magnitude, the centermost value is median of sample within the window, is a filter output.

**c) Image Enhancement**: The objective of image enhancement is to process an image to increase visibility of feature of interest. Here contrast enhancement is used to get better quality result.

3**. Image Segmentation** Image segmentation are of many types such as clustering, threshold, neural network based and edge based. In this implementation we are using the clustering algorithm called mean shift clustering for image segmentation. This algorithm uses the sliding window method for converging to the Centre of maximum dense area. This algorithm makes use of many sliding windows to converge the maximum dense region. Mean shift clustering Algorithm This algorithm is mainly used for detecting highly dense region.

**Feature Extraction:**

There are many features of an image mainly color, texture, and shape. Here we are considering three features that are color histogram, Texture which resembles color, shape, and texture.

**5. Training** Training dataset was created from images of known Cancer stages. Classifiers are trained on the created trainingdataset. A testing dataset is placed in a temporary folder. Predicted results from the test case, Plots classifiers graphs and add feature-sets to test case file, to make image processing models more accurate

**6. Classification** The binary classifier which makes use of the hyper-plane which is also called as the decision boundary between two of the classes is called as Convolution Neural Network. Some of the problems are pattern recognition like texture classification makes use of CNN. Mapping of nonlinear input data to the linear data provides good classification in high dimensional space in CNN. The marginal distance is maximized between different classes by CNN. Different Kernels are usedto divide the classes. CNN is basically a binary classifier that determines hyper plane in dividing two classes. The boundary is maximized between the hyperplane and two classes. The samples that are nearest to the margin will be selected in determining the hyperplane is called support vectors.

**Hardware and Software Requirements:**

## Hardware:

System : Pentium IV 2.4 GHz or More .

Hard Disk : 40 GB.

Monitor : 15 VGA Colour.

Mouse : Logitech.

Ram : 1Gb

**Software:**

Python

Keras

Tensorflow

Numpy

Pandas

Matplotlib

OpenCV

h5py

imgaug

**Expected Outcomes:**

* Detection of Input Image
* Classification of image
* Detection of retinopathy images
* Remedies

**Applications:**

* It can be used in diagnosis centers
* In Eye Hospitals

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