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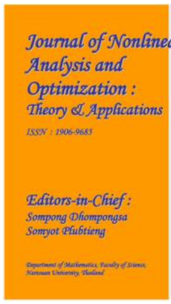

MULTI-CLASS RETINAL DISEASES DETECTION USING DEEP CNN WITH MINIMAL MEMORY CONSUMPTION

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Abstract:
Artificial Neural Networks (ANN), Deep learning, Recurrent Neural Networks (RNN), Alex Net, and ResNet can be seen as a broad study field in the diagnosis and categorization of severe diseases. The way medical disorders are classified, particularly those pertaining to the retina, has been transformed by CNN and its particular variation, which is referred to as U-Net Segmentation. When sending the complete feature map to the associated decoder, U-Net has a considerable inaccuracy in memory and CPU usage due to the complexity of feature extraction. Furthermore, merging it with the unsampled decoder feature map keeps pooling indices from being reused. In this study, we propose a memory-efficient convolutional neural network (CNN) model for multi-class classification issues. The suggested model has been assessed using the Eye Net standard benchmark dataset, which includes 32 kinds of retinal disorders. The results of the experimental evaluation indicate that the accuracy and memory management of the suggested model are better. A comprehensive comparison has been conducted using varying epoch counts, time consumption for each step, and precision, recall, and accuracy. The suggested method performed well on the Eye-net dataset in terms of accuracy.

1.Introduction

The most prevalent disease in humans, skin cancer, is mostly diagnosed visually. A clinical screening is done first, and then a dermoscopic study, biopsy, and histological examination may be necessary. Because skin lesions can vary widely in their appearance, automatically classifying them from photographs is a difficult challenge. For a wide range of fine-grained object classifications, deep convolutional neural networks (CNNs)4,5 have promise for broad and highly variable tasks6,7,8,9,10,11. In this example, we show how to classify skin lesions with a single CNN that was trained end-to-end from photos using just pixels and disease labels as inputs. 129,450 clinical images—two orders of magnitude greater than earlier datasets12—that represent 2,032 distinct diseases are used to train a CNN. We evaluate its efficacy using two crucial binary classification use cases, keratinocyte carcinomas vs benign seborrhoeic keratoses and malignant melanomas versus benign nevi, on biopsy-proven clinical pictures, against 21 board-certified dermatologists. The first case illustrates the most prevalent types of cancer, while the second illustrates the skin cancer with the highest fatality rate. In both tests, the CNN performs as well as all tested specialists, proving that artificial intelligence is capable of classifying skin cancer at a level of proficiency that is on par with dermatologists. Deep neural networks on mobile devices may enable dermatologists to reach patients outside of their clinics. By 2021, it's estimated that 6.3 billion people will have smartphone subscriptions (ref. 13). This might mean that everyone will have affordable access to essential diagnostic care. Due to a sharp rise in blood glucose levels, diabetic retinopathy (DR), which affects the eyes, has grown more common in recent times. Almost half of all adults under 70 suffer from serious diabetes worldwide. Patients with DR often lose their vision if appropriate treatment and early diagnosis are not received. Once the warning signals have been identified, the disease's severity level must be confirmed in order to make decisions about future therapy. In the current study paper, the idea of classifying DR fundus photos using a deep learning model according to severity degree is explored. In this paper, an automatic detection and classification approach for fundus DR pictures based on deep learning is proposed. Preprocessing, segmentation, and classification are the three procedures that are involved in the suggested method. The preprocessing step of the approach involves removing any extraneous noise from the edges. Subsequently, the image is segmented using a histogram to extract the regions of interest. Next, the DR fundus images were classified into different severity levels using the Synergic Deep Learning (SDL) model. The Messidor DR dataset was used to justify the SDL model that was given. The experimental findings showed that compared to the previous models, the proposed SDL model provides superior categorization. This research provides a deep learning-based feature extraction method for retina-based illness diagnosis. This procedure aids in the development of an automated screening system that can identify conditions affecting the retina, including retinitis pigmentosa, retinoblastoma, macular detachment, age-related molecular degeneration, and diabetic retinopathy. It is challenging to classify some of these diseases because they have a common feature. A multi-class SVM classifier and deep learning feature extraction are utilised to solve the aforementioned issue. This work's primary contribution is the reduction of the dimensions of the attributes needed to categorise retinal diseases, which improves both system performance and the process of lowering system requirements. A condition known as diabetic retinopathy (DR) is a rise in blood glucose that affects the eyes. Diabetes is a factor in 50% of fatalities among individuals over the age of 70. For many DR patients, the amount of vision loss can be decreased with early detection and adequate treatment. After DR symptoms are identified, the disease's severity should be assessed to determine the appropriate course of treatment. This work focuses on the use of convolutional neural networks with appropriate Pooling, Softmax, and Rectified Linear Activation Unit (ReLU) layers to achieve a high degree of accuracy in the categorization of DR fundus images based on the severity of the illness. The Messidor database has been used to verify the suggested algorithm's performance. Classification accuracies of 96.6% and 96.2%, 95.6% and 96.6% have been attained for healthy pictures and images of stages 1, 2, and 3 of diabetic retinopathy. Goal To establish quantitative markers for intermediate age-related macular degeneration (AMD) in older persons using spectral-domain optical coherence tomography (SD-OCT) imaging. Create Technology and diagnostic test evaluation. Players and Regulators One eye from the Age-Related Eye Disease Study 2 (AREDS2) Ancillary SD-OCT Study, which included 269 patients with intermediate AMD and 115 elderly subjects without AMD. Techniques The axial distance between the apex of the drusen and RPE layer and Bruch's membrane is known as the RPE drusen complex (RPEDC), and the axial distance between the inner limiting and Bruch's membranes is known as the total retina (TR). These limits were semiautomatically determined. To create a map of "normal" non-AMD thickness, we registered and averaged the thickness maps from the control participants. RPEDC thicknesses greater than or less than three standard deviations from the mean were regarded as abnormal and were indicative of geographic atrophy (GA) or drusen, respectively. For every patient, we measured their TR volumes, RPEDC volumes, and aberrant RPEDC thickening and thinning volumes. Based on the generalised linear model regression framework, we created five automatic classifiers for the presence of AMD by combining different combinations of these four disease markers. We used the leave-one-out approach to train and assess these classifiers' performance. Principal Outcome Measures The thicknesses of RPEDC and TR in a 5-mm-diameter cylinder centred at the fovea, together with their range and topographic distribution. Outcomes All four disease indications were needed for the most effective way to distinguish between AMD and control eyes. For this classifier, the receiver operating characteristic's (ROC) area under the curve (AUC) was more than 0.99. The overall neurosensory retinal thickness in AMD-affected versus control eyes in our study differs from smaller-scale investigations that have been conducted before. In conclusion Using a large atlas of eyes, we analysed the topographic distribution of normal and aberrant RPEDC thicknesses to identify and test effective biometrics to differentiate AMD from normal eyes. To share the 38 400 SD-

OCT images, accompanying segmentations, and quantitative measures from this investigation, we have developed an online atlas [1-15].

2. Proposed System

For multi-class classification issues, we suggest a convolutional neural network (CNN) model that makes effective use of memory use. The suggested model has been assessed using the Eye Net standard benchmark dataset, which includes 32 kinds of retinal disorders. The deep learning-based CNN model has been used to improve the traditional diagnostic approach for retinal-based critical disorders. The suggested CNN model is compared to conventional state-of-the-art methods. A comprehensive comparison has been conducted by evaluating precision, recall, and accuracy across varying epoch counts and step times.

1. According to the material given, our investigation doesn't specifically address the segmentation strategy that was employed. But if it employs a more sophisticated segmentation technique, it could be able to isolate essential features more accurately.
2. A convolutional neural network (CNN) model, a popular and adaptable architecture for image classification applications, is used in our work. CNNs are a great option for classifying retinal diseases because they are well-established and have shown successful in a variety of applications.
3. The CNN model is made to utilise memory resources effectively. This implies that our approach may provide a more resource-efficient and optimised solution, which can be essential for scalability and real-world implementation.

2.1 System design

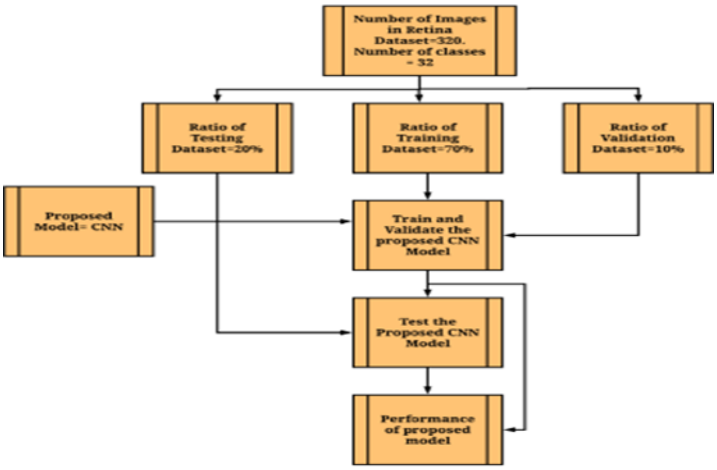

Figure.1. System architecture

DATA FLOW DIAGRAM

1. Another name for the DFD is a bubble chart. A system can be represented using this straightforward graphical formalism in terms of the input data it receives, the different operations it performs on that data, and the output data it generates.
2. One of the most crucial modelling tools is the data flow diagram (DFD). The components of the system are modelled using it. These elements consist of the system's procedure, the data it uses, an outside party that communicates with it, and the information flows within it.
3. DFD illustrates the flow of information through the system and the various changes that alter it. This method uses graphics to show how information flows and the changes made to data as it goes from input to output.
4. Another name for DFD is a bubble chart. Any level of abstraction can be utilised to portray a system using a DFD. DFD can be divided into phases that correspond to escalating functional detail and information flow.

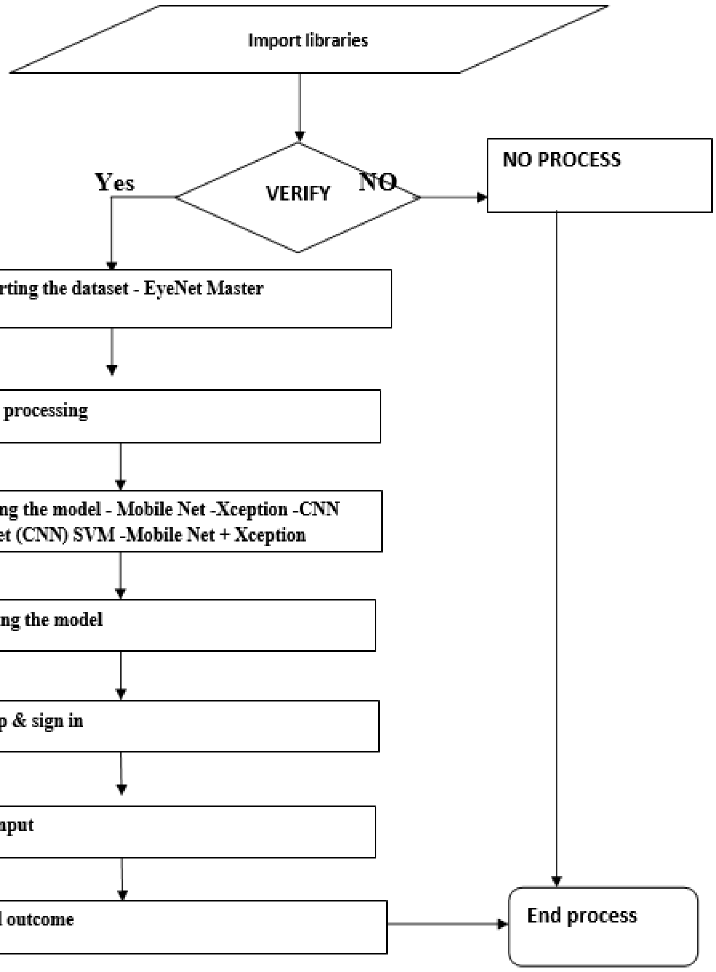

Figure.2. Data flow diagram

2.2 UML DIAGRAMS

Unified Modelling Language is known as UML. An industry-standard general-purpose modelling language used in object-oriented software engineering is called UML. The Object Management Group developed and oversees the standard.

The intention is for UML to spread as a standard language for modelling object-oriented software. The two main parts of UML as it exists now are a notation and a meta-model. In the future, UML may also include other processes or methods that are connected to it.

A common language for business modelling and other non-software systems, as well as for defining, visualising, building, and documenting software system artefacts, is called the Unified Modelling Language.

The following are the main objectives of the UML design:

1. Give users access to an expressive, ready-to-use visual modelling language so they can create and share valuable models.
2. To expand the fundamental ideas, offer methods for specialisation and extendibility.
3. Be unaffected by specific development processes or programming languages.
4. Offer an official foundation for comprehending the modelling language.
5. Promote the market expansion for OO tools.
6. Encourage the use of higher level development ideas like components, frameworks, partnerships, and patterns.
7. Combine the finest techniques.

2.3Use case diagram

According to the Unified Modelling Language (UML), a use case diagram is a particular kind of behavioural diagram that is produced from and defined by a use case study. Its objective is to provide a graphical summary of the functionality that a system offers in terms of actors, use cases (representations of their goals), and any interdependencies among those use cases. A use case diagram's primary goal is to display which actors receive which system functionalities. It is possible to illustrate the roles of the system's actors.

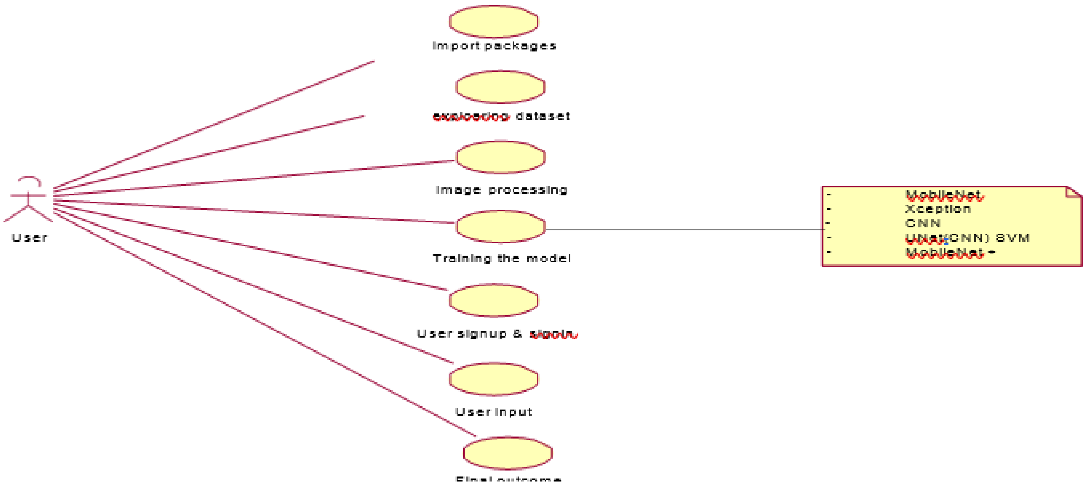

Figure.3. Use Case diagram

2.4Class diagram:

The use case diagram and the system's comprehensive design are both improved by the class diagram. The actors identified in the use case diagram are categorised into a number of related classes by the class diagram. There are two types of relationships that can exist between the classes: "is-a" relationships and "has-a" relationships. It's possible that every class in the class diagram can perform certain functions. The "methods" of the class refer to these features that it offers. In addition, every class might possess specific "attributes" that allow for class uniqueness.

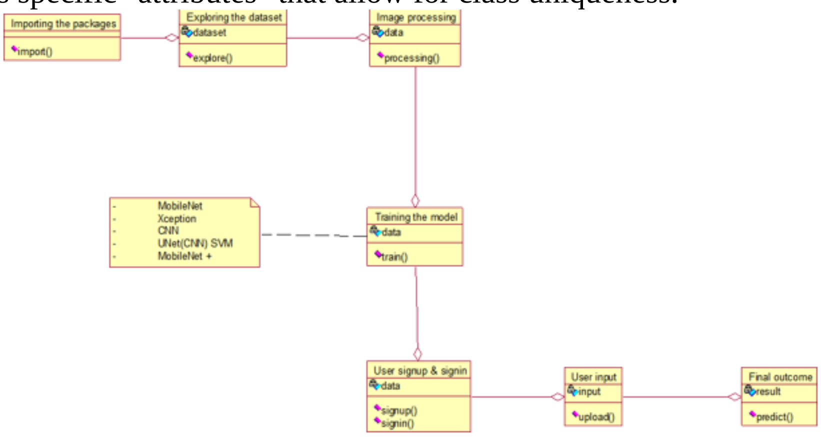

Figure.4. Class diagram

2.5 Activity diagram

The activity diagram shows how the system's processes are organised. An activity diagram has the same elements as a state diagram: activities, actions, guard conditions, initial and final states, and transitions.

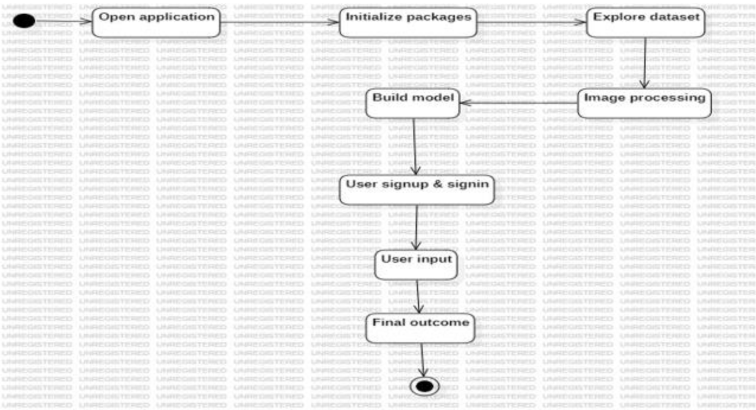

Figure.5. Activity diagram

2.6 Sequence diagram

The way various system items interact with one another is depicted in a sequence diagram. A sequence diagram's time-ordering is one of its key features. This indicates that a step-by-step representation of the precise order in which the items interacted is provided. In the sequence diagram, various objects communicate with one another by sending "messages".

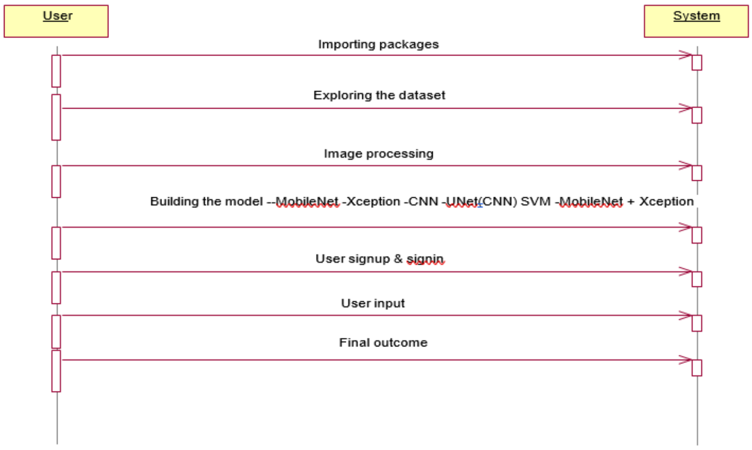

Figure.6. Sequence diagram

2.7 Collaboration diagram

A cooperation diagram combines the ways in which various things interact with one another. To make it easier to follow the order of the encounters, they are listed as numbered interactions. All potential interactions between each object and other objects are identified with the aid of the cooperation diagram.

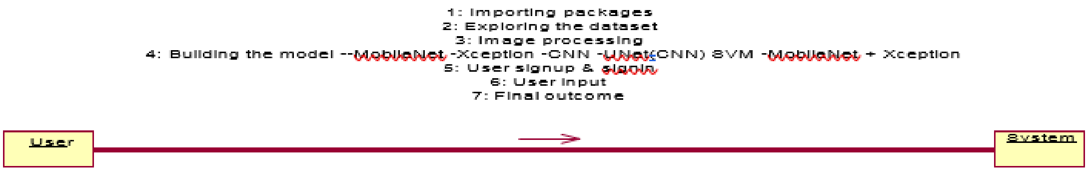

Figure.7. Collaboration diagram

2.8 Component diagram

The high-level components that comprise the system are represented in the component diagram. A high-level representation of the system's components and their relationships is shown in this diagram. The parts removed from the system after it has completed the development or manufacturing stage are shown in a component diagram.

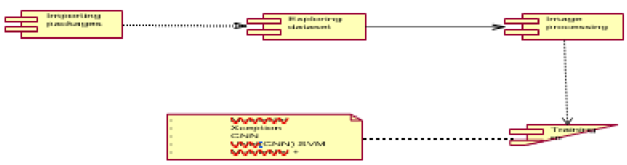

Figure.8. Component diagram

2.9 Deployment diagram

The deployment diagram captures the configuration of the runtime elements of the application. This diagram is by far most useful when a system is built and ready to be deployed.

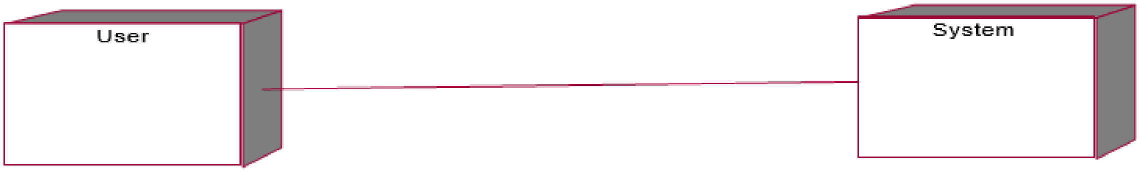

Figure.9. Deployment diagram

2.10 SYSTEM TESTING

System testing is the process by which a quality assurance (QA) team assesses how the many components of an application interact with one another in the complete, integrated system or application. It is also known as system-level testing or system-integration testing. System testing confirms that a programme works as intended. This phase, which is a form of "black box" testing, is concerned with an application's functioning. For instance, system testing might verify that all user input results in the desired output across the application.

System testing phases: A video guide for this particular test level. System testing looks at each and every part of an application to ensure that it functions as a cohesive whole. System testing is usually carried out by a quality assurance team following the examination of individual modules through functional or user-story testing, followed by integration testing for each component

Before a software build is put into production, where users use it, it undergoes acceptance testing to make sure it meets all requirements set forth in system testing. A team working on app development keeps track of all errors and decides what sorts and quantities are acceptable.

2.11 Software Testing Strategies:

The greatest strategy to make software engineering testing more effective is to optimise the approach. A software testing plan outlines the steps that must be taken in order to produce a high-quality final product, including what, when, and how. To accomplish this main goal, the following software testing techniques—as well as their combinations—are typically employed:

Static Examination:

Static testing is an early-stage testing approach that is carried out without really operating the development product. In essence, desk-checking is necessary to find errors and problems in the code itself. This kind of pre-deployment inspection is crucial since it helps prevent issues brought on by coding errors and deficiencies in the software's structure.

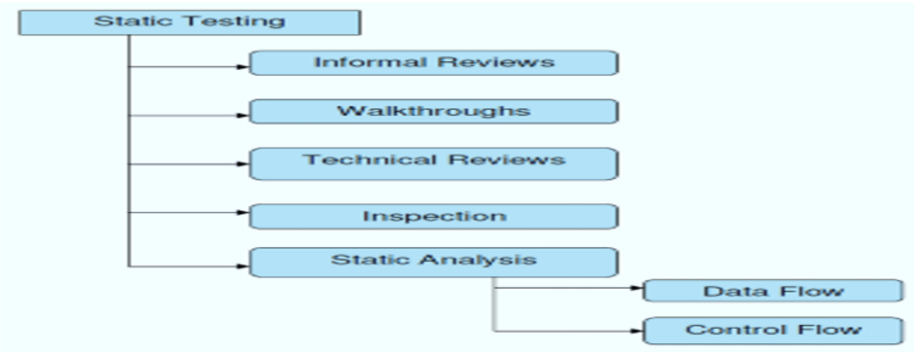

Figure.10. Static Testing

2.12 Structural Testing

Software cannot be tested efficiently unless it is run. White-box testing, another name for structural testing, is necessary to find and correct flaws and faults that surface during the pre-production phase of the software development process. Regression testing is being used for unit testing depending on the programme structure. To expedite the development process at this point, it is typically an automated procedure operating inside the test automation framework. With complete access to the software's architecture and data flows (data flows testing), developers and quality assurance engineers are able to monitor any alterations (mutation testing) in the behaviour of the system by contrasting the test results with those of earlier iterations (control flow testing).

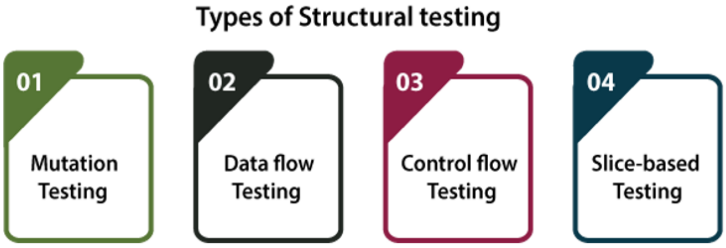

Figure.11. Structural Testing

2.13 Behavioural Testing

Rather than the mechanics underlying these reactions, the final testing phase concentrates on how the programme responds to different activities. Put differently, behavioural testing, commonly referred to as black-box testing, relies on conducting multiple tests, the majority of which are manual, in order to examine the product from the perspective of the user. In order to perform usability tests and respond to faults in a manner similar to that of ordinary users of the product, quality assurance engineers typically possess specialised information about a company or other purposes of the software, sometimes known as "the black box." If repetitive tasks are necessary, behavioural testing may also involve automation (regression tests) to remove human error. To see how the product handles an activity like filling out 100 registration forms on the internet, for instance, it would be better if this test were automated.

Figure.12. Behavioural Testing

3. Results and Discussion

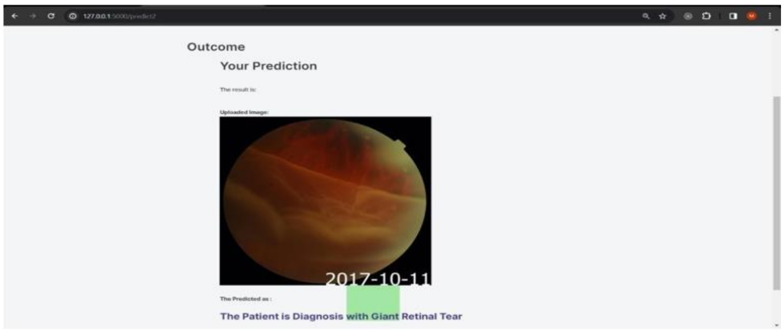

Figure.13. Result 1

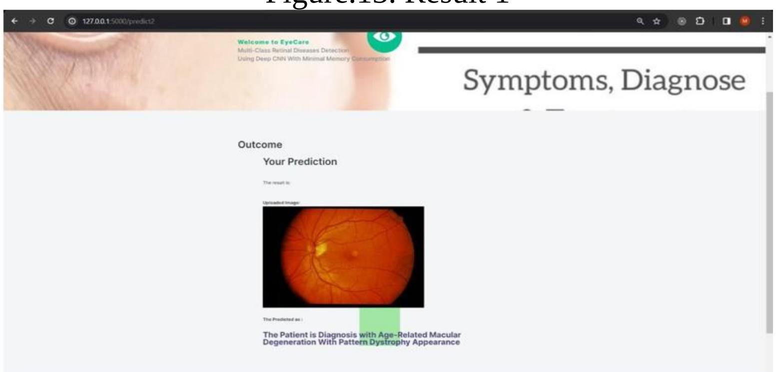

Figure.14. Result 2

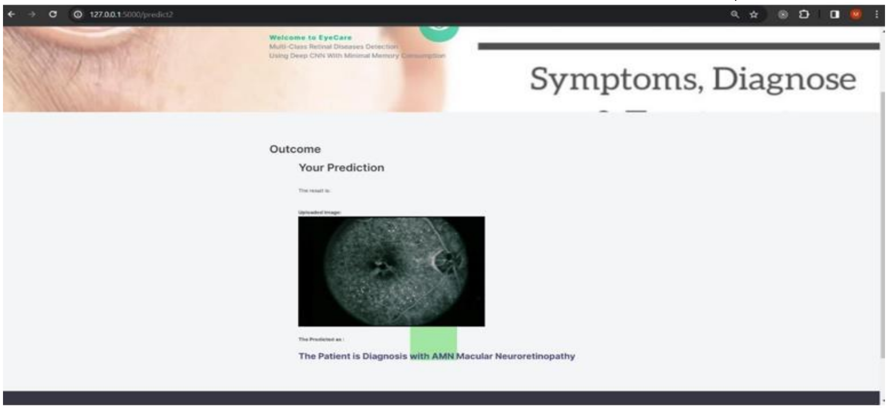

Figure.15. Result 3

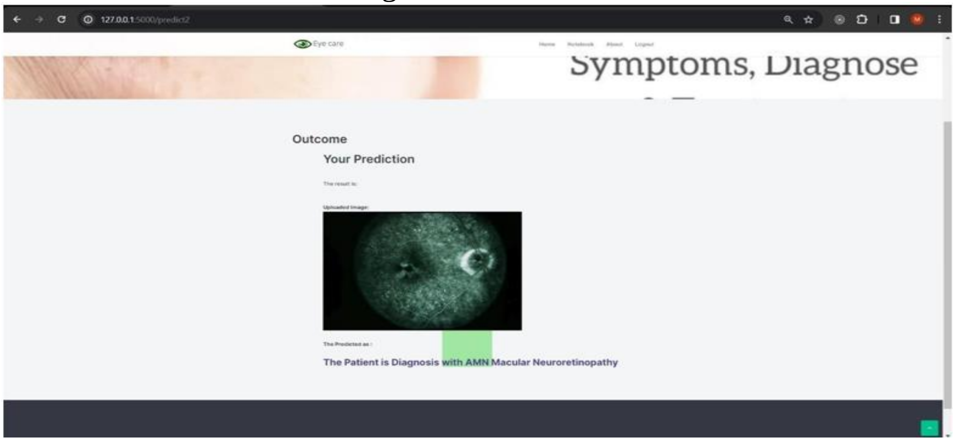

Figure.16. Result 4

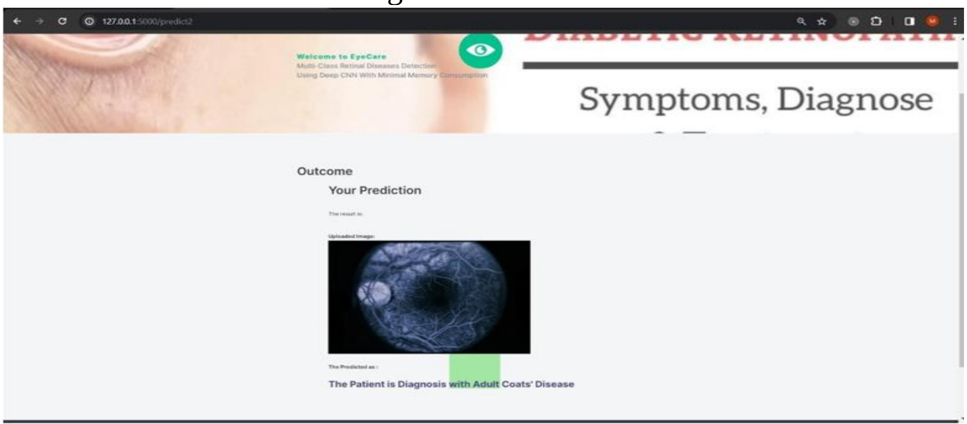

Figure.17. Result 5

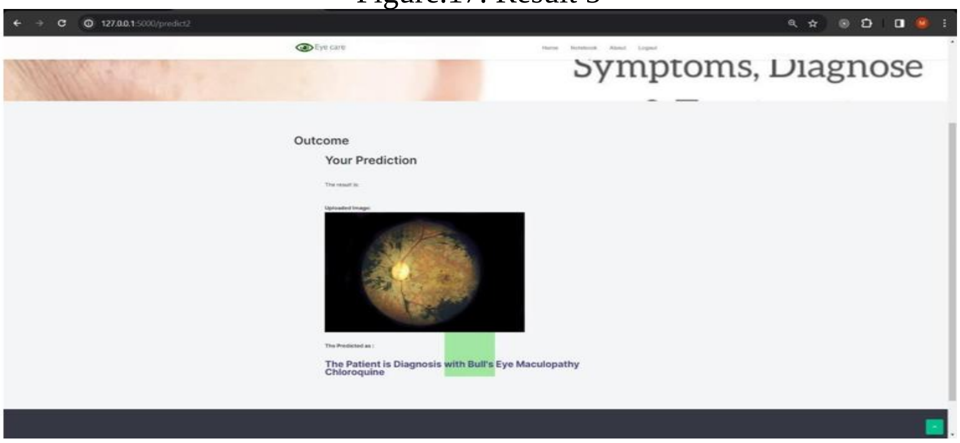

Figure.18. Result 6

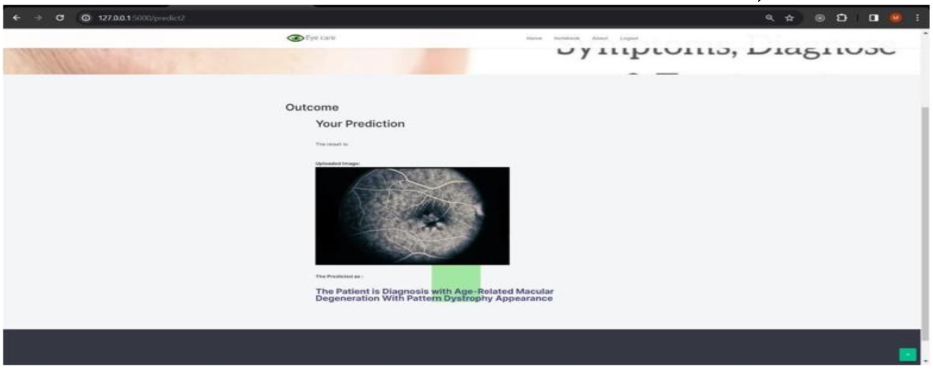

Figure.19. Result 7

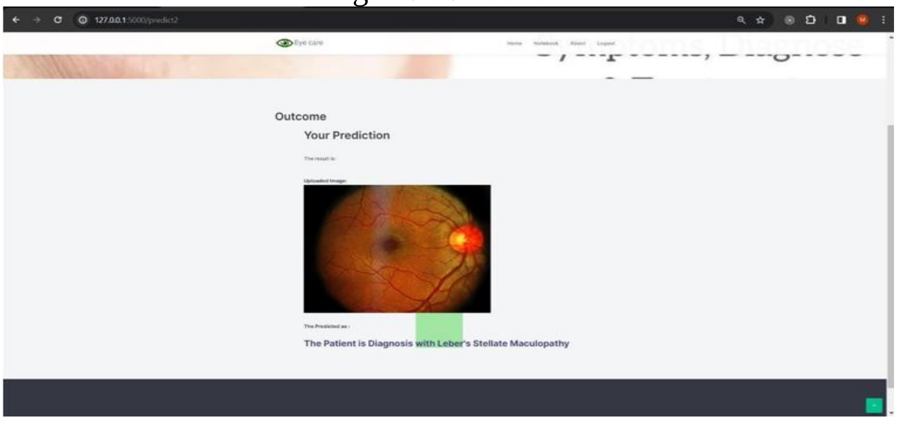

Figure.20. Result 8

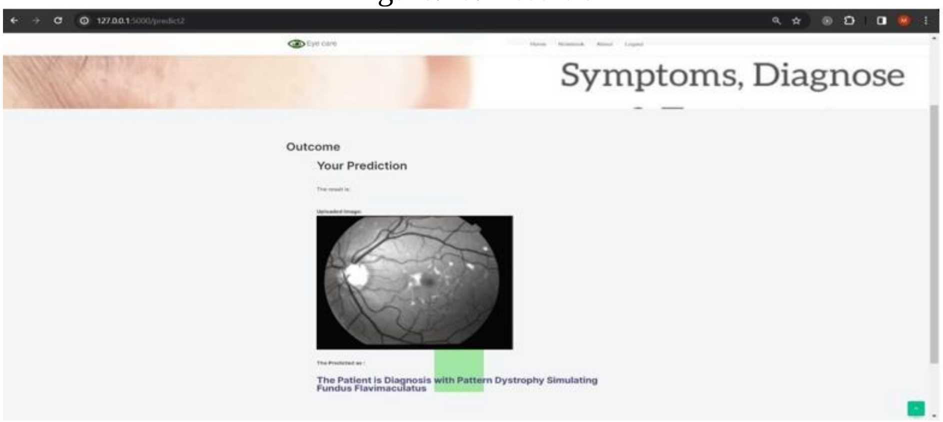

Figure.21. Result 9

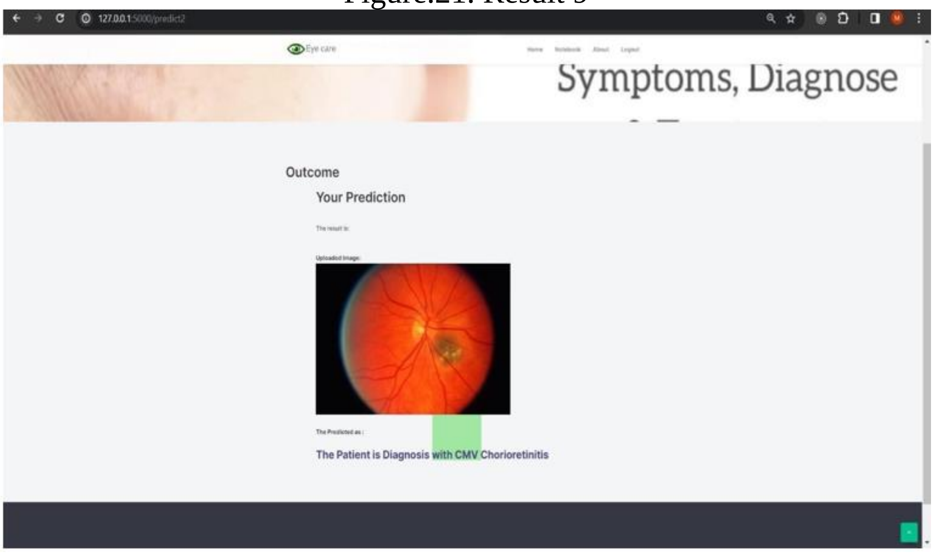

Figure.22. Result 10

4. Conclusion

A CNN model based on deep learning is presented in order to address the categorization of the various retinal illnesses. The model's execution is based on EyeNet, a dataset with 32 distinct retinal disorders. To assess the model's correctness, it is trained across many epochs. The model was first trained at 10 epochs and produced high validation accuracy; it then produced the same validation accuracy with a different validation loss of 0.0279 at 15 epochs. The model performs significantly better overall than other models regarded as state-of-the-art. It is possible that the model presented will be useful in the classification of retinal disorders. Updating the model on a regular basis and retraining it with fresh data will keep improving performance. This will be accomplished by taking advantage of the developments in deep learning methods and the growing amount of datasets related to retinal diseases.

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