A.V.C COLLEGE OF ENGINEERING

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

OCULAR DISEASE PROGNOSIS USING DEEP LEARNING

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ABSTRACT

- Retinal pathologies are the most common cause of childhood blindness worldwide. Rapid and automatic detection of diseases is critical and urgent in reducing the ophthalmologist's workload. Ophthalmologists diagnose diseases based on pattern recognition through direct or indirect visualization of the eye and its surrounding structures. Dependence on the fundus of the eye and its analysis make the field of ophthalmology perfectly suited to benefit from deep learning algorithms. Each disease has different stages of severity that can be deduced by verifying the existence of specific lesions and each lesion is characterized by certain morphological features where several lesions of different pathologies have similar characteristics. We note that patients may be simultaneously affected by various pathologies, and consequently, the detection of eye diseases has a multi-label classification with a complex resolution principle.
- Two deep learning solutions are being studied for the automatic detection of multiple eye diseases. The solutions chosen are due to their higher performance and final score in the ILSVRC challenge: Inception V3 (GoogleNet) and VGGNet. First, we study the different characteristics of lesions and define the fundamental steps of data processing. We then identify the software and hardware needed to execute deep learning solutions. Finally, we investigate the principles of experimentation involved in evaluating the various methods, the public database used for the training and validation phases, and report the final detection accuracy with other important metrics.

INTRODUCTION

- Ocular prognosis holds immense significance in the field of healthcare, influencing treatment decisions and patient outcomes.
- Leveraging the power of deep learning, a groundbreaking approach emerges to revolutionize ocular prognostication.
- This methodology harnesses the capabilities of artificial intelligence to analyze complex ocular data with unparalleled precision.
- By integrating deep learning algorithms, we aim to enhance diagnostic accuracy, identify disease features in ocular conditions, and provide a proactive approach to treatment planning.
- This technology not only promises to redefine prognostic accuracy but also improves personalized healthcare and effective eye care.

LITERATURE SURVEY

S. No	Title	Author	Journal Name	Year	Techniques	Merits	Demerits
1.	Deep learning for automatic detection of diabetic retinopathy in retinal fundus photographs.	Gulshan V, Peng L, Coram M	JAMA.	2016.	Utilized a deep learning algorithm to detect diabetic retinopathy in retinal fundus photographs. The algorithm employed a CNN architecture trained on a large dataset of images.	Achieved high accuracy in detecting diabetic retinopathy, potentially aiding in early diagnosis and intervention.	Limited to diabetic retinopathy detection and may not generalize well to other ocular diseases.
2.	Automated detection of diabetic retinopathy using deep learning.	Ting DSW, Cheung CY, Lim G	Ophthal mology.	2017	Developed a deep learning algorithm for automated detection of diabetic retinopathy using a CNN architecture trained on a large dataset of retinal images.	Demonstrated high sensitivity and specificity in detecting diabetic retinopathy, enabling early intervention and prevention of vision loss.	May require further validation in real-world clinical settings to assess generalizatio n and reliability.

3.	Deep learning approach for hyper tension detection in retinal images.	Gulshan V, Rajan RP, Widner K	IEEE Transactions on Medical Imaging.	2018.	Proposed a deep learning approach for diabetic retinopathy detection using a CNN architecture trained on a large-scale dataset of retinal images.	hieved high accuracy and sensitivity in detecting hyper tension, potentially improving screening efficiency and reducing the burden on healthcare systems.	Relies heavily on the quality and diversity of the training dataset, which may affect generalization to other populations or ocular diseases.
4.	Deep learning for automated glaucoma detection in retinal fundus photographs.	Kauppi T, Kalesnykiene V, Kamarainen JK	Survey of Ophthalmology.	2020	Reviewed various deep learning approaches for automated glaucoma detection in retinal fundus photographs, including CNN architectures trained on large datasets.	Highlighted the potential of deep learning in improving glaucoma diagnosis accuracy and efficiency, leading to early detection and treatment.	Emphasized the need for further validation and standardization of deep learning algorithms for clinical use, as well as addressing challenges related to interpretability and data privacy.

5.	Deep learning-based detection of age-related macular degeneration in retinal images: A review.	Wong CW, Tsai A, Jonas JB	Eye.	2020	Reviewed deep learning approaches for detecting age-related macular degeneration (AMD) in retinal images, including CNN architectures trained on large datasets.	Identified the potential of deep learning in automated AMD detection, facilitating early diagnosis and treatment to prevent vision loss.	Discussed challenges such as dataset bias, model interpretability, and the need for real-world clinical validation, emphasizing the importance of addressing these issues for widespread clinical adoption.
6.	Review on the application of deep learning in the diagnosis of glaucoma from fundus images.	Lee R, Chung H, Lim J	Journal of Ophthalmology.	2021	reviewed the application of deep learning techniques for diagnosing glaucoma from fundus images, focusing on CNN architectures trained on large-scale datasets.	Highlighted the potential of deep learning in improving glaucoma diagnosis accuracy and efficiency, enabling early detection and treatment to prevent vision loss.	The study emphasized the importance of addressing challenges in model interpretability, dataset bias, and real-world clinical validation to ensure successful implementation of deep learning models in clinical practice.

EXISTING SYSTEM

- Existing employs imaged processing algorithms to analyze eye images and identify early signs of Diabetics Retinopathy.
- Through feature extraction and pattern recognition, this method enhances diagnostic process.
- The integration of machine learning enhances the system's ability to adapt and refine its detection capabilities over time.

DRAWBACKS:

- Variations in image quality and lighting conditions
- False positives or negatives can occur, leading to misdiagnoses
- Potential delays in treatment.

PROBLEM IDENTIFICATION

- Accuracy Enhancing the system's accuracy is vital for reducing misdiagnoses and ensuring early detection. This involves refining image processing algorithms and machine learning models to better identify retinal abnormalities accurately.

- Enhancement: Improving the interpretability of the system's decisions is crucial for gaining trust from healthcare professionals. Methods to explain the rationale behind the system's predictions should be developed to enhance clinicians' understanding and validation of its recommendations.

- Data Standardization: Standardizing the analysis process for retinal images and addressing variability in image quality is essential for ensuring the system's reliability across different datasets and patient populations. Robust data preprocessing techniques and quality control measures can enhance consistency and reliability.

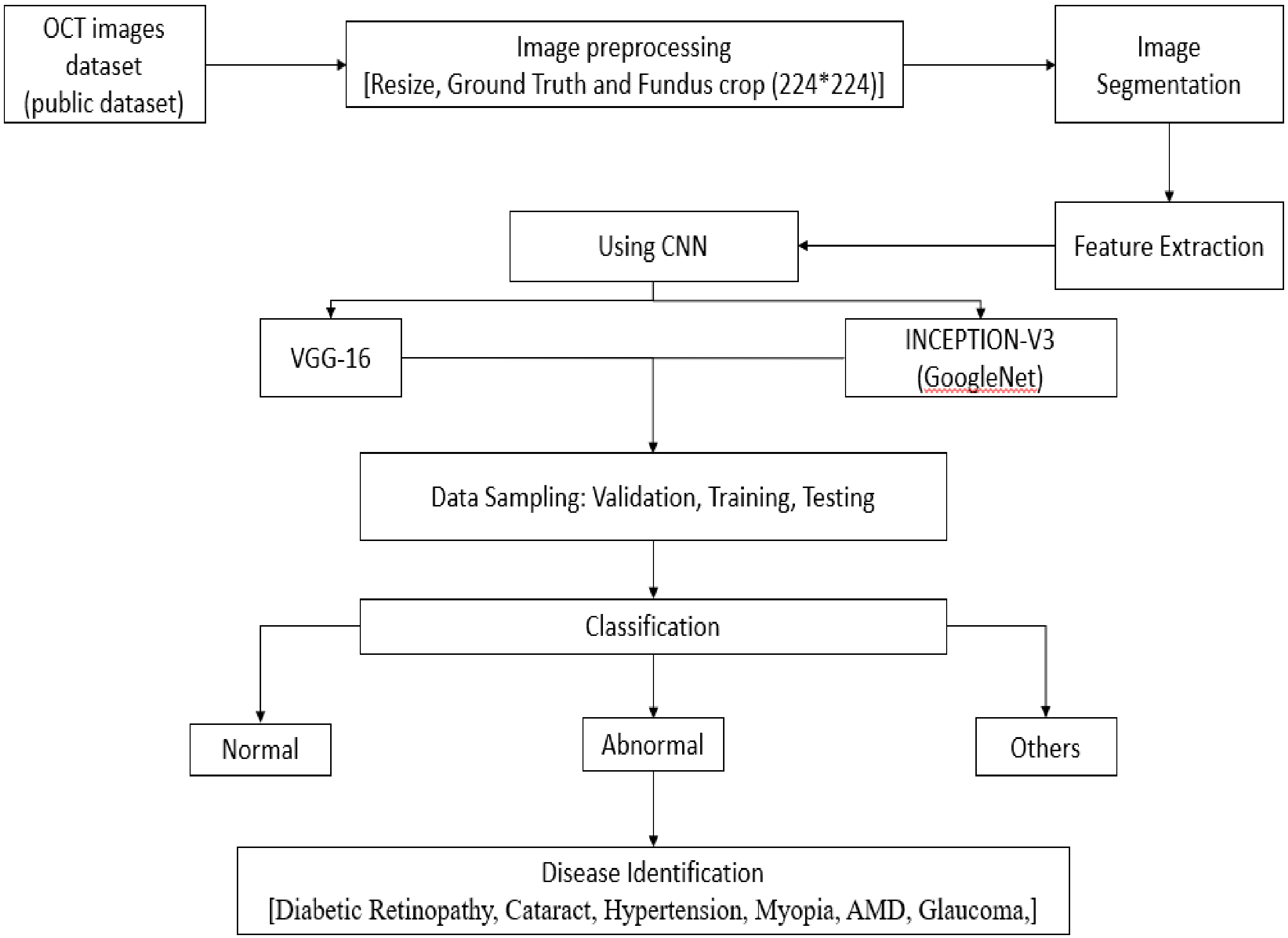
- Integration with Clinical Workflow: Seamless integration into existing clinical workflows is necessary for the system's practical implementation. Compatibility with electronic health record systems and providing actionable insights in an accessible format can facilitate adoption and use in routine clinical practice

OBJECTIVE

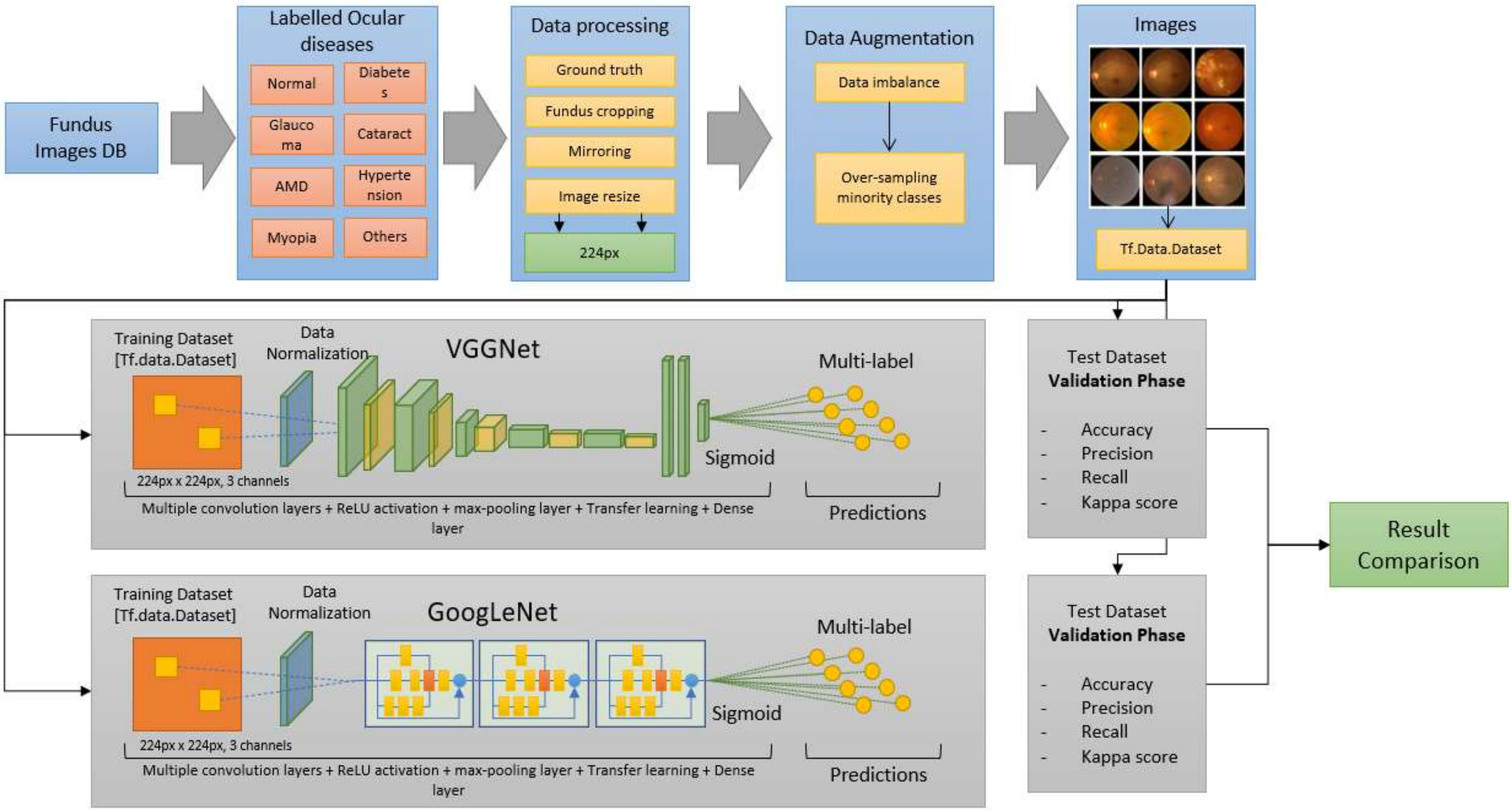
- To Expand the capabilities of existing deep learning algorithms to classify multiple eye diseases and abnormalities, including diabetic retinopathy, cataract, hypertension, pathological myopia, glaucoma, and others, in resource-constrained settings.

- Develop efficient and scalable methodologies for data processing, model training, and evaluation, while ensuring high accuracy and reliability in disease detection.

ARCHITECTURE DIAGRAM



ARCHITECTURE



Work Flow

1) Trained Dataset

2) Testing Dataset

3) Data Preprocessing

4) Data Augmentation

SAMPLE IMAGES

Diabetic Retinopathy

- Blurry double vision,
- Dark floating spots

Hyper tension

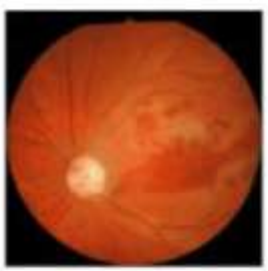
- Double vision
- dim vision

Myopia

•Squint to see clearly.
•Eye strain

AMD- Age Related Macular Degeneration

•Blur the central vision



Glaucoma

- Slow vision loss

Cataract

- Blurry vision

Normal

- Normal

METHODOLOGY OF PROPOSED WORK

1. Data Collection and Preparation: Compile a diverse dataset of ocular images representing various diseases, meticulously annotated and standardized for format, size, and quality.

2. Deep Learning Model Selection Choose a suitable convolutional neural network (CNN) architecture for image classification tasks, partitioning the dataset into training, validation, and test subsets.

3. Model Training and Validation: Train the deep learning model iteratively, extracting relevant features from ocular images and preventing overfitting through fine-tuning of parameters.

4. Performance Evaluation: Rigorously evaluate the trained model's performance using metrics such as accuracy, precision, recall, F1 score, and AUC-ROC against test datasets and real-world clinical data.

5. Integration and Deployment: Integrate the trained model into a user-friendly software application for real-time ocular disease identification, enabling healthcare providers to make informed decisions and facilitate timely interventions.

6. Continuous Monitoring and Maintenance: Maintain the deployed system's reliability and effectiveness over time through continuous monitoring, user feedback, updates, and improvements, ensuring compliance with regulatory standards and patient safety.

MODULES

- **VGG16**

VGG16 is a convolutional neural network (CNN) architecture that was developed by the Visual Geometry Group (VGG) at the University of Oxford. It's a part of the VGG family of models and is widely used for image classification tasks. VGG16 consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. It's known for its simplicity and uniform architecture, where the convolutional layers have 3x3 filters and are followed by max-pooling layers. VGG16 achieved good performance on image classification benchmarks like ImageNet.

- **INCEPTION-V3**

Inception-v3 is a convolutional neural network architecture developed by Google as part of the Inception family of models. It's designed for image recognition and classification tasks. Inception-v3 is characterized by its deep architecture and its extensive use of inception modules. These modules are responsible for performing different types of convolutions (1x1, 3x3, 5x5) concurrently and then concatenating their outputs, enabling the network to capture features at multiple scales efficiently. Inception-v3 also incorporates other techniques such as batch normalization and factorized 7x7 convolutions to improve training speed and performance. It has been widely used for various computer vision tasks and has achieved excellent results on benchmark datasets like ImageNet.

- **Training and Validation Module**

Trains the deep learning model using annotated ocular data. This module involves splitting the dataset into training, validation, and possibly test sets, training the model on the training data, tuning hyper parameters, and evaluating model performance on the validation set. Techniques such as transfer learning or fine-tuning pre-trained models may also be employed to expedite training and improve generalization.

- **Eye Disease Classification Module**

Implements the classification algorithm utilizing the trained deep learning model to classify ocular images into different disease categories. This module predicts the presence and severity of eye diseases such as diabetic retinopathy, cataract, hypertension, pathological myopia, glaucoma, and other abnormalities based on the learned features extracted by the deep learning model.

- **Performance Evaluation Module**

Evaluates the performance of the developed framework in terms of diagnostic precision, sensitivity, specificity, and other relevant metrics. This module assesses the accuracy, reliability, and generalization ability of the deep learning model in correctly identifying and classifying various eye diseases and abnormalities.

THE ULTIMATE FINDING OF THE PROJECT

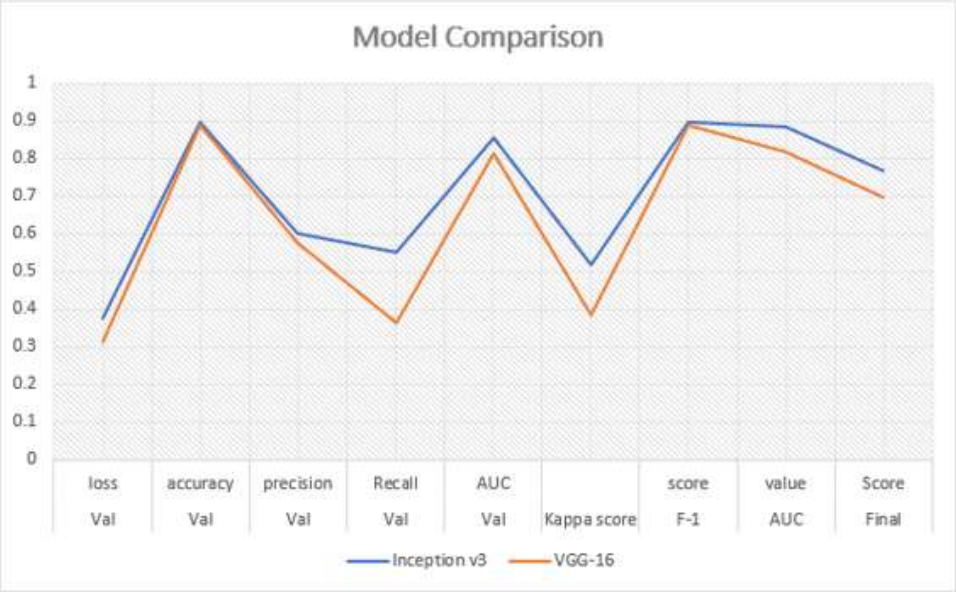
- **Accuracy and Efficacy:** Validation of the deep learning model's accuracy and efficacy in identifying various ocular diseases through high-performance metrics.
- **Clinical Relevance:** Demonstration of the system's diagnostic predictions aligning with clinical diagnoses, validating its utility in real-world clinical practice.
- **Impact on Patient Outcomes:** Contribution to improved patient outcomes, reduced healthcare costs, and enhanced quality of care through early detection and personalized treatment planning.
- **Comparative Analysis:** Demonstration of superior performance, efficiency, or scalability compared to existing systems, validating its potential as a state-of-the-art solution.
- **Generalization and Robustness:** Consistent performance and reliability in diverse real-world scenarios, validating its potential for widespread adoption and deployment.
- **Future Directions and Recommendations:** Identification of limitations, challenges, and opportunities for improvement, along with proposed strategies for enhancing the system's capabilities and adaptability over time.

MODELS COMPARISION TABLE

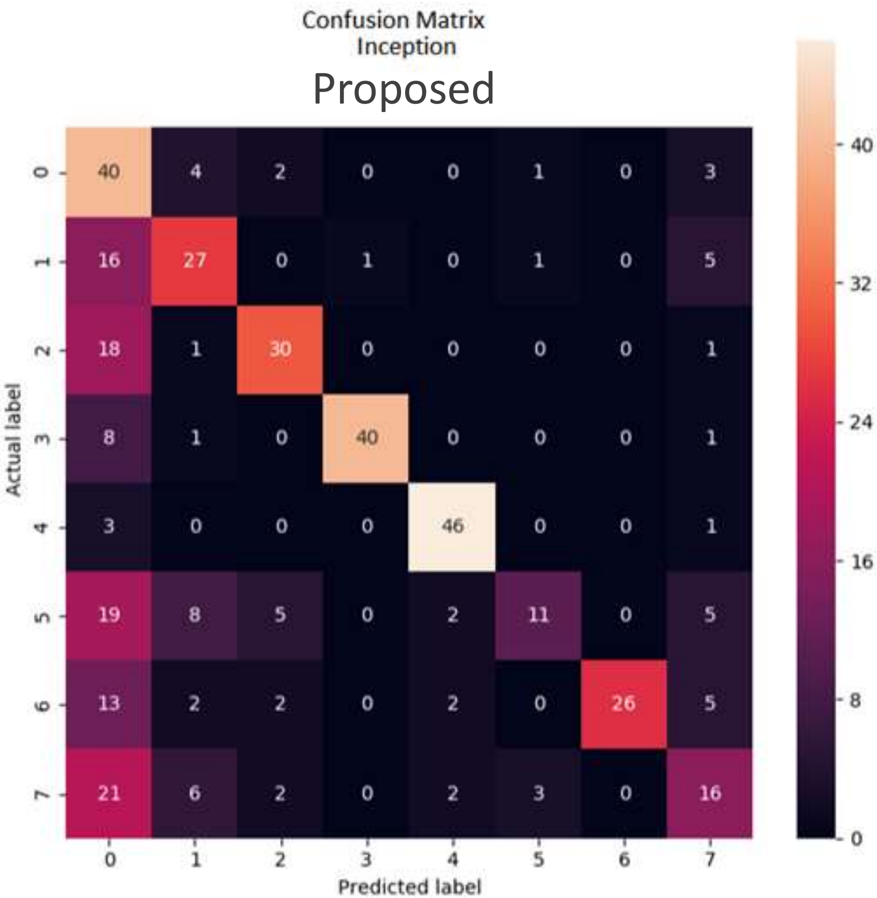
	Proposed	Existing
Training Detail	**Inception v3**	**VGG-16**
Data Augmentation	Yes	Yes
Transfer Learning	Yes	Yes
Weights	Pre-trained on ImageNet	Pre-trained on ImageNet
Last Layer	GlobalAveragePooling2D Dense (1024, activation='relu') Dense (8, activation='sigmoid')	Dense (8, activation='sigmoid')
Feature Extraction Enabled	Yes	No
Classification Enabled	Yes	Yes
Optimizer	SGD lr=0.01, decay=1e-6, momentum=0.9, nesterov=True	SGD lr=0.001, decay=1e-6, momentum=0.9, nesterov=True
Loss function	Binary Cross-Entropy	Binary Cross-Entropy
Early Stopping patience	8 steps for validation loss, type [min]	8 steps for validation loss, type [min]
Number of Parameters	23,909,160	134,293,320
Number of trainable Parameters	23,874,728	32,776

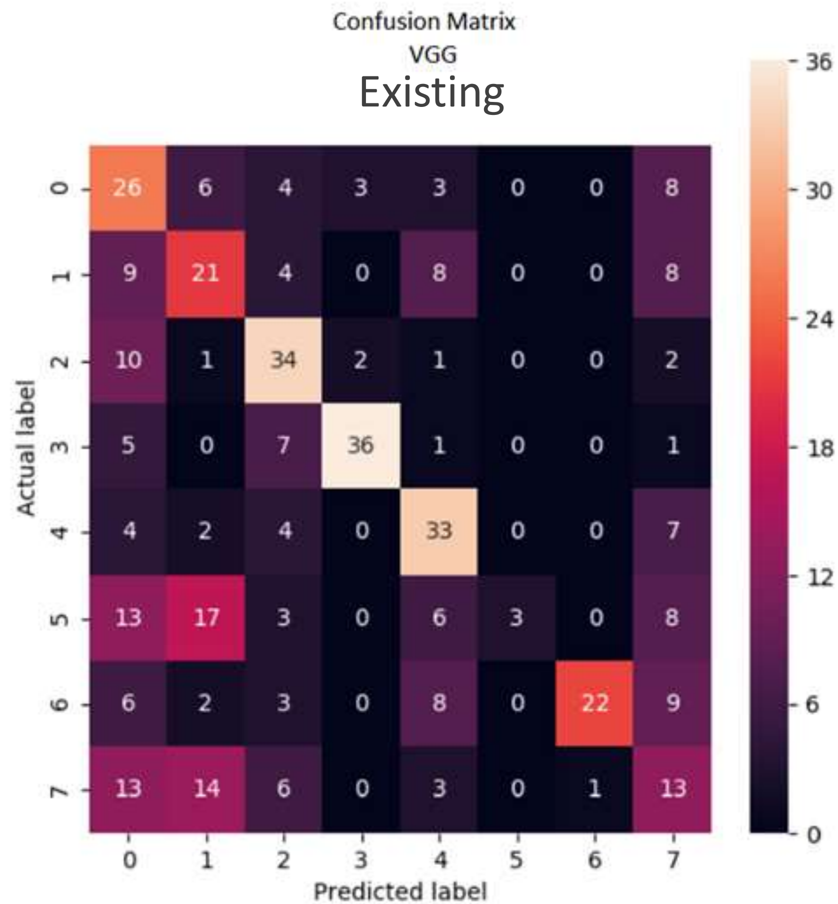
PERFORMANCE ANALYSIS

Model	Val loss	Val accuracy	Val precision	Val Recall	Val AUC	Kappa score	F-1 score	AUC value	Final Score
Inception v3 Proposed	0.3769	0.8984	0.6021	0.552	0.855	0.5186	0.8984	0.8838	0.7669
VGG-16 Existing	0.3137	0.8871	0.5776	0.3625	0.8140	0.3863	0.8871	0.8176	0.6970

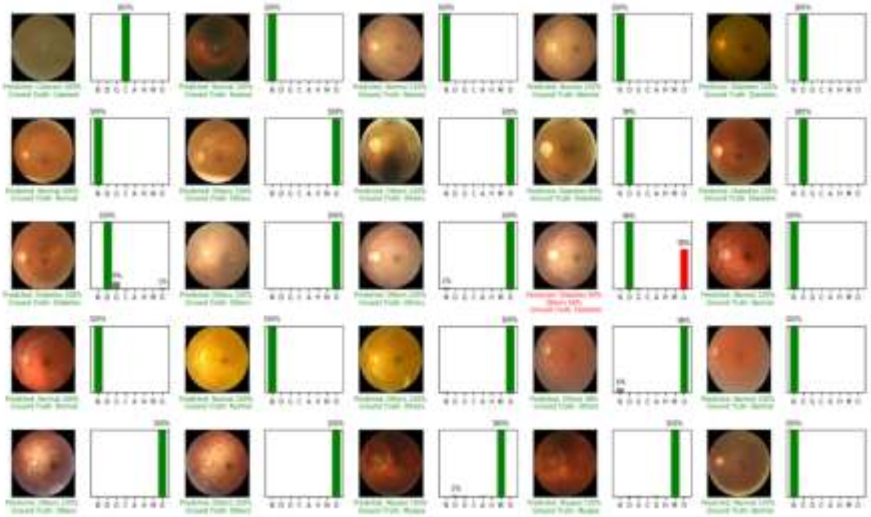


CONFUSION MATRIX



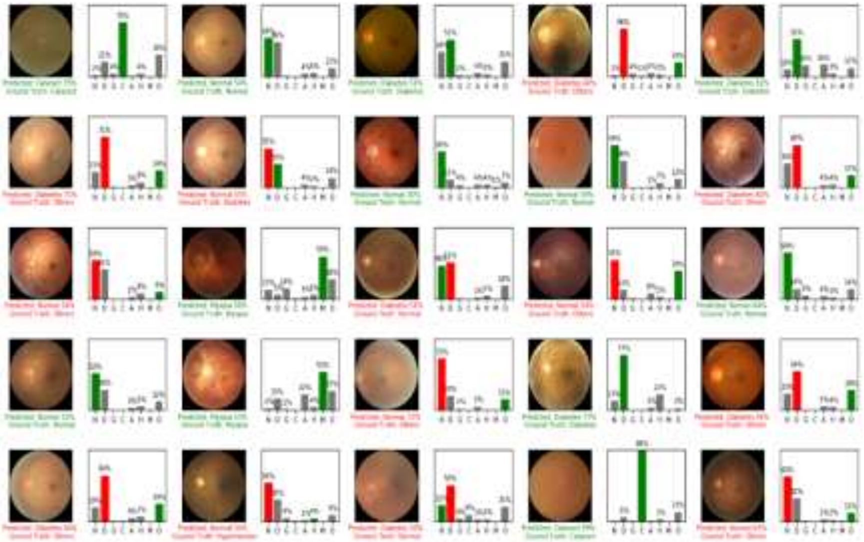


CLASSIFICATION OUTPUT



INCEPTION-V3

VGG-16



RESULTS OF DEEP LEARNING MODELS

```
400/400 - 59s - loss: 0.3014 - accuracy: 0.8759 - precision: 0.5064 - recall
: 0.2975 - auc: 0.8188
loss :  0.3014095723628998
accuracy :  0.8759375
precision :  0.506383
recall :  0.2975
auc :  0.81879866

C:\Users\yokesh\AppData\Local\Programs\Python\Python37\lib\site-packages\skl
earn\metrics\classification.py:564: DeprecationWarning: `np.int` is a deprec
ated alias for the builtin `int`. To silence this warning, use `int` by itse
lf. Doing this will not modify any behavior and is safe. When replacing `np.
int`, you may wish to use e.g. `np.int64` or `np.int32` to specify the preci
sion. If you wish to review your current use, check the release note link fo
r additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/d
evdocs/release/1.20.0-notes.html#deprecations
  w_mat = np.ones([n_classes, n_classes], dtype=np.int)
Kappa score: 0.311062906724512
F-1 score: 0.8759375
AUC value: 0.8188919642857143
Final Score: 0.6686307903367421
```

VGG-16
RESULTS EVALUATION

INCEPTION-V3
RESULTS EVALUATION

```
400/400 - 24s - loss: 0.0264 - accuracy: 0.9897 - precision: 0.9465 - recall
: 0.9725 - auc: 0.9977
loss :  0.026424899417907
accuracy :  0.9896875
precision :  0.94647205
recall :  0.9725
auc :  0.99774003

C:\Users\yokesh\AppData\Local\Programs\Python\Python37\lib\site-packages\skl
earn\metrics\classification.py:564: DeprecationWarning: `np.int` is a deprec
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lf. Doing this will not modify any behavior and is safe. When replacing `np.
int`, you may wish to use e.g. `np.int64` or `np.int32` to specify the preci
sion. If you wish to review your current use, check the release note link fo
r additional information.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/d
evdocs/release/1.20.0-notes.html#deprecations
  w_mat = np.ones([n_classes, n_classes], dtype=np.int)
Kappa score: 0.9534062830921285
F-1 score: 0.9896875
AUC value: 0.9989473214285715
Final Score: 0.9806803681735667
```
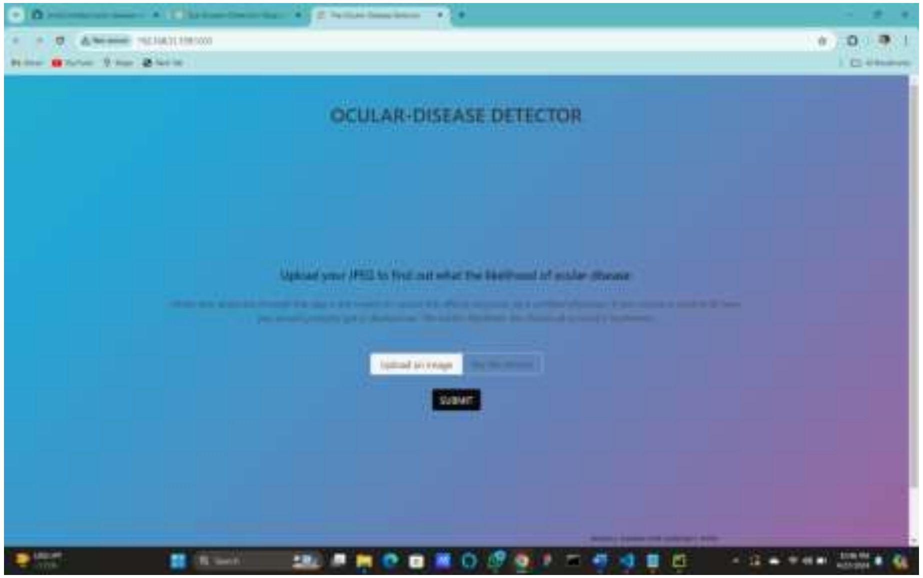
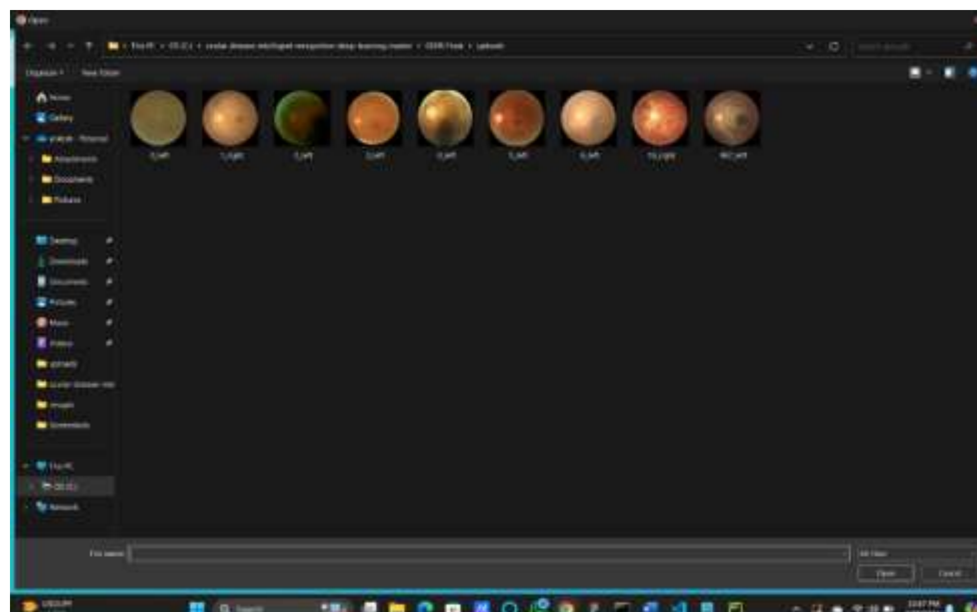

WEB APPLICATION



1.WEB HOME PAGE

2.WEB UPLOADS FOLDER



WEB APPLICATION- OUTPUTS

3. OUTPUT SAMPLE-1

4. OUTPUT SAMPLE-2

CONCLUSION

In conclusion, this project has demonstrated the potential of deep learning algorithms in automating the detection of eye diseases, particularly in the context of retinal pathology. By leveraging advanced machine learning techniques and state-of-the-art models such as Inception-v3 and VGG16, significant progress has been made towards reducing the workload of ophthalmologists and improving diagnostic accuracy.

Through extensive experimentation and evaluation, we have achieved promising results in the automated classification of multiple eye diseases, achieving high accuracy and robustness in multi-label classification tasks. The comparative analysis between Inception-v3 and VGG16 has provided valuable insights into the strengths and weaknesses of each architecture, guiding future research and development efforts.

Furthermore, the deployment of a web application using Flask framework for interactive image selection and result visualization enhances the accessibility and usability of the system, facilitating seamless integration into clinical workflows.

REFERENCES

[1] Mao, Yuxing, Yinghong He, Lumei Liu, and Xueshuo Chen. "Disease classification based on synthesis of multiple long short-term memory classifiers corresponding to eye movement features." IEEE Access 8 (2020).

[2] J. Bradshaw, F. Shic, A. N. Holden, E. J. Horowitz, A. C. Barrett, T. C. German, and T. W. Vernon, ‘‘The use of eye tracking as a biomarker of treatment outcome in a pilot randomized clinical trial for young children with autism,’’ Autism Res., vol. 12, no. 5, pp. 779–793, May 2019.

[3] K. Feil, N. Boettcher, O. Kremmyda, C. Muth, J. Teufel, A. Zwergal, T. Brandt, and M. Strupp, ‘‘Pharmacotherapy of vestibular disorders, nystagmus and cerebellar disorders,’’ Laryngo-Rhino-Otologie, vol. 97, no. 1, pp. 14–23, 2018.

[4] C. K. Sheehy, E. Bensinger, A. Romeo, L. Rani, B. Shi, J. M. Gelfand, S. B. Stevenson, and A. J. Green, ‘‘High fidelity fixational eye movements as a novel potential biomarker for disability in multiple sclerosis,’’ Multiple Sclerosis J., vol. 24, no. 2, pp. 572–573, 2018.

[5] M. Murias, S. Major, K. Davlantis, L. Franz, A. Harris, B. Rardin, M. Sabatos-DeVito, and G. Dawson, ‘‘Validation of eye-tracking measures of social attention as a potential biomarker for autism clinical trials,’’ Autism Res., vol. 11, no. 1, pp. 166–174, Jan. 2018.

[6] O. Kremmyda, S. Bardins, A. Straube, and T. Eggert, ‘‘Changes in quick phases of downbeat nystagmus during visual fixation,’’ J. Neurol., vol. 264, no. S1, pp. S93–S95, Oct. 2017.

[7] J. H. Rim, S.-T. Lee, H. Y. Gee, B. J. Lee, J. R. Choi, H. W. Park, S.-H. Han, and J. Han, ‘‘Accuracy of next-generation sequencing for molecular diagnosis in patients with infantile nystagmus syndrome,’’ JAMA Ophthalmology, vol. 135, no. 12, pp. 1376–1385, 2017.

[8] N. I. Vargas-Cuentas, A. Roman-Gonzalez, R. H. Gilman, F. Barrientos, J. Ting, D. Hidalgo, K. Jensen, and M. Zimic, ‘‘Developing an eye-tracking algorithm as a potential tool for early diagnosis of autism spectrum disorder in children,’’ PLOS ONE, vol. 12, no. 11, pp. 1–13, 2017.

[9] O. A. Coubard, ‘‘What do we know about eye movements in Alzheimer’s disease? The past 37 years and future directions,’’ Biomarkers Med., vol. 10, no. 7, pp. 677–680, Jul. 2016.

REFERENCES

[10] J. Wei, J. Fang, and W. Zhao, ''Word learning with multiple cues in children with autistic spectrum disorder: Evidence from eye movements,'' Acta Psychologica Sinica, vol. 46, no. 3, pp. 385–395, 2014.

[11] S. Lu, J. Xu, M. Li, J. Xue, X. Lu, L. Feng, B. Fu, G. Wang, N. Zhong, and B. Hu, ''Attentional bias scores in patients with depression and effects of age: A controlled, eye-tracking study,'' J. Int. Med. Res., vol. 45, no. 5, pp. 1518–1527, Oct. 2017.

[12] M. Li, S. Lu, G. Wang, L. Feng, B. Fu, and N. Zhong, ''Alleviated negative rather than positive attentional bias in patients with depression in remission: An eye-tracking study,'' J. Int. Med. Res., vol. 44, no. 5, pp. 1072–1086, Oct. 2016.

[13] A. Duque and C. Vazquez, ''A failure to show the efficacy of a dot-probe attentional training in dysphoria: Evidence from an eye-tracking study,'' J. Clin. Psychol., vol. 74, no. 12, pp. 2145–2160, Dec. 2018.

[14] X. Xu, X. Lyu, X. Chang, and Y. Yu, ''Exploration of eye movement of depressive disorder liver Qi stagnation syndrome patients,'' Chin. Arch. Traditional Chin. Med., vol. 35, no. 4, pp. 889–891, 2017.

[15] M. Hunfalvay, ''Eye tracking as a biomarker for concussion,'' J. Head Trauma Rehabil., vol. 35, no. 2, pp. E183–E184, 2020.

[16] C. Liu, Q. Zhang, and W. Cai, ''The parameters of eye-track in patients with mental disorder due to brain damage,'' Forensic Sci. Int., vol. 277, no. 1, p. 64, 2017.

[17] F. Jagla, ''Saccadic eye movements as a marker of mental disorders,'' Physiological Res., pp. S365–S371, Oct. 2016.

[18] S. Brakemeier, A. Sprenger, I. Meyhöfer, J. E. McDowell, L. H. Rubin, S. K. Hill, M. S. Keshavan, G. D. Pearlson, C. A. Tamminga, E. S. Gershon, and S. S. Keedy, ''Smooth pursuit eye movement deficits as a biomarker for psychotic features in bipolar disorder—Findings from the PARDIP study,'' Bipolar Disorders, pp. 1–10, 2019. [Online]. Available: https://onlinelibrary.wiley.com/doi/pdfdirect/10.1111/bdi.12865

REFERENCES

[19] J. E. Silberg, I. Agtzidis, M. Startsev, T. Fasshauer, K. Silling, A. Sprenger, M. Dorr, and R. Lencer, ‘‘Free visual exploration of natural movies in schizophrenia,’’ Eur. Arch. Psychiatry Clin. Neurosci., vol. 269, pp. 407–418, Jan. 2018.

[20] K. Morita, K. Miura, M. Fujimoto, H. Yamamori, Y. Yasuda, M. Iwase, K. Kasai, and R. Hashimoto, ‘‘Eye movement as a biomarker of schizophrenia: Using an integrated eye movement score,’’ Psychiatry Clin. Neurosci., vol. 71, no. 2, pp. 104–114, Feb. 2017.

[21] S. Dowiasch, B. Backasch, W. Einhäuser, D. Leube, T. Kircher, and F. Bremmer, ‘‘Eye movements of patients with schizophrenia in a natural environment,’’ Eur. Arch. Psychiatry Clin. Neurosci., vol. 266, no. 1, pp. 43–54, Feb. 2016.

[22] X. Yangyang, Z. Tianhong, W. Jijun, and X. Zeping, ‘‘Research progress of smooth pursuit eye movement in schizophrenia,’’ J. Int. Psychiatry, vol. 44, no. 3, pp. 395–397, 2017.

[23] Y. Luo, P. Xitian, X. Shuai, and L. Hongying, ‘‘An eye tracker used for the detection of schizophrenia,’’ Beijing Biomed. Eng., vol. 35, no. 6, pp. 639–644, 2016.

[24] J. K. H. Lim, Q.-X. Li, Z. He, A. J. Vingrys, V. H. Wong, N. Currier, J. Mullen, B. V. Bui, and C. T. Nguyen, ‘‘The eye as a biomarker for Alzheimer’s disease,’’ Frontiers Neurosci., vol. 10, no. 536, pp. 1–14, 2016


THANK YOU!