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AN EFFECTIVE PREDICTIVE MODEL FOR OCULAR MELANOMA DETECTION USINGDEEP LEARNING APPROACH

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Eye Melanoma is one of the deadliest cancers in the world. In 95% of cases, there's a high chance of survival for cases if diagnosed with a veritably early stage of melanoma. Still, the discovery of this complaint is just as delicate and rare as optical melanoma is. Despite the existing techniques to detect ocular melanoma, it is prevalent that patients are still vulnerable to it due to rare causes and malignancy as well as due to the availability of fewer diagnostic techniques for ocular melanoma. Due to the lack of skilled dermatologists globally diagnosis of any disease related to melanoma is normally based on visual inspection, and hence different machine learning and deep learning algorithms are used to develop models for detecting ocular melanoma. Deep learning-based algorithms are designed to assist ophthalmologists and pathologists in the timely and accurate diagnosis of ocular melanoma to establish a real-time detection model.

Keywords: AlexNet, DenseNet201, EfficientNetB0, InceptionResNetV2, VGG16.

1. Introduction

The Deep Learning algorithms are efficient in Ocular Melanoma Detection, especially Convolutional Neural Networks (CNN). They can automatically extract and learn complex visual features from medical images, handle high-dimensional data efficiently, and maintain robustness to variability in image conditions, enhancing diagnostic accuracy and speed. The early detection of Ocular Melanoma helps in a faster and higher rate of recovery since it is known to be the deadliest.

1.1. Literature Survey

The literature survey provides an overview of recent advancements in melanoma and ocular melanoma detection highlighting the deep-learning architectures and techniques used so far. For instance, studies have proposed deep learning models such as CNN augmented with Modified ResNet50 to classify skin lesions (Alwakid *et al.*, 2022). Another innovative fusion of CNN with transfer learning has shown higher accuracy (Abbes and Sellami, 2021). Basic CNN architecture models such as DenseNet, VGG, and AlexNet has been used in the detection of ocular melanoma (Ganguly *et al.*, 2019). Research of melanoma detection using CNN architectures such as MobileNetV2 and DenseNet and comparative analysis was proposed with higher accuracy (Moturi *et al.*, 2024).

An ensemble approach to different DL models such as LSTM and GRU has also been made to overcome specific challenges in detecting cutaneous melanoma promising to provide good results (Ali Shah *et al.*, 2023). Techniques such as using a pre-trained frozen base model and a trainable head model, a self-boosting framework proposed to refine usage in imbalanced datasets (Indraswari *et al.*, 2022). Contourlet Transform (CT) and Local Binary Pattern (LBP) are combined and used for skin cancer image analysis, optimizing feature selection with Particle Swarm Optimization (PSO) to reduce dimensionality. These feature sets are then applied to ML algorithms to achieve better results. (Natha and Rajeswari 2023).

Additionally, the DL techniques along with pooling give better results (Tawheed *et al.*, 2021; Naqvi *et al.*, 2023). These endeavors emphasize the collaborative efforts between AI researchers and healthcare professionals, aiming to seamlessly integrate advanced technologies into clinical workflows to enhance patient care and diagnostic accuracy. Furthermore, deep neural networks along with transfer learning are a fused approach towards melanoma detection (Abbes and Sellami, 2021).

The survey includes various DL and CNN models to improvise the existing models with future upgrades. Further enrich the insights into specific methodologies and their applications in ocular melanoma detection.

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2. Proposed Methodology

2.1. Predictive Model Architecture

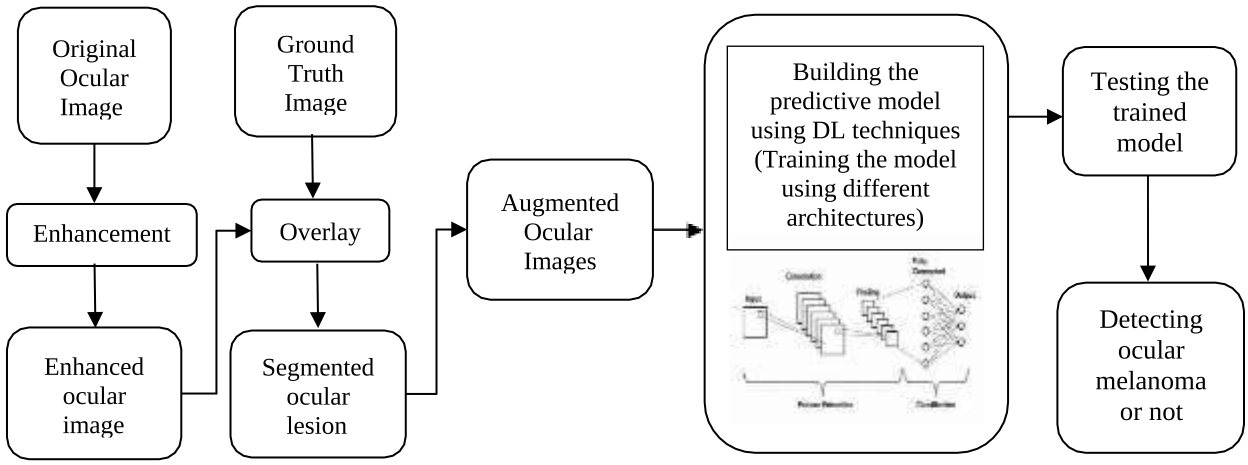

Fig.1. System Architecture of the Proposed Predictive Model.

The system architecture is the critical tool that identifies key components such as image preprocessing, feature extraction, classification algorithms, and result visualization, elucidating their roles and relationships inside the system. Thus, an architecture diagram plays a vital role in ocular melanoma detection, guiding the development process and ensuring the system's efficacy, efficiency, and sustainability, fostering communication, collaboration, evaluation, and improvement throughout the development and deployment process as shown in Fig.1.

2.2. Flowchart of the Predictive Model

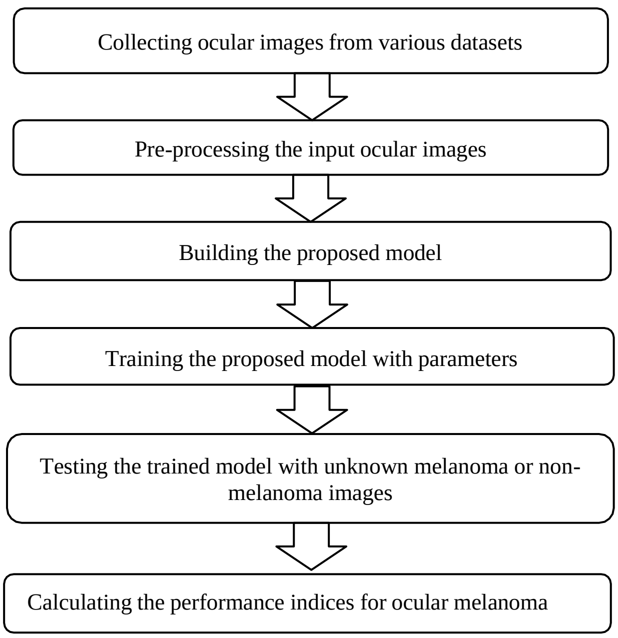

Fig.2. Flowchart of the Predictive Model.

Collecting ocular images from various datasets that are certified by medical experts for model training and building. Pre-processing the collected ocular images involves cropping and resizing the images to make them suitable for the model training and building. Building the model by training the existing CNN models to obtain the proposed work, i.e., to detect ocular melanoma. Hence, the collected datasets are pre-processed and classified in the 80-20 ratio. 80% of the datasets are used for model training based on different parameters. Testing of each model with the remaining 20% of collected ocular datasets with unknown ocular images to detect melanoma or not. Finally, the calculation of the performance metrics for ocular melanoma classification using various CNN architectures as shown in Fig.2. The ocular images have been collected from New York Eye Cancer Center database.

2.3. Algorithm of the Predictive Model

The predictive model involves the following sequence:

Algorithm. Ocular Melanoma Detection

Step 1. Collect various ocular images.
Step 2. Pre-process the collected ocular images.
Step 3. Train various CNN architectures using the 80% of the collected ocular images.
Step 4. Test the trained models using the 20% of the ocular images.
Step 5. Evaluate the performance of the models.
Step 6. Analyze the result and generate comparison graph.

3. Experimental Results and Discussion

The proposed work involves specific hardware and software requirements. The hardware requirements are 8 GB RAM, an Intel CORE i5 Processor, and an Intel 4 GB GPU. The software requirements are Windows 11 Operating System as processing platform where the programming language used is Python.

3.1. Evaluation Metrics

The confusion matrix components such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are used for the evaluation metrics. The performance metrics can be calculated to assess the model's classification as follows:

i. **Accuracy:** The proportion of correctly classified instances out of the total instances is called accuracy and can be calculated using Eq. [1].

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad [1]$$

ii. **Precision:** The proportion of true positive predictions out of all positive predictions made by the model is called precision and can be calculated using Eq. [2].

$$Precision = \frac{TP}{(TP+FP)} \quad [2]$$

iii. **Recall (Sensitivity):** The proportion of true positive predictions out of all actual positive instances is called recall or sensitivity and can be calculated using Eq. [3].

$$Recall = \frac{TP}{(TP+FN)} \quad [3]$$

iv. **Specificity:** The proportion of true negative predictions out of all actual negative instances is called specificity and can be calculated using Eq. [4].

$$Specificity = \frac{TP}{(TP+FN)} \quad [4]$$

v. **F1 Score:** The harmonic mean of precision and recall, providing a balance between the two metrics is called the F1 score and can be calculated using Eq. [5].

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad [5]$$

3.2. Performance Evaluation of the Predictive Model

The predictive model is trained with the following five CNN architectures - InceptionResNetV2, DenseNet201, AlexNet, VGG16, and EfficientNetB0 efficiently for ocular melanoma detection to provide good results; These models are assessed, and their accuracy graphs and confusion matrix screenshots are attached as follows:

i. InceptionResNetV2

Fig.3. Graph showing the accuracy obtained using InceptionResNetV2.

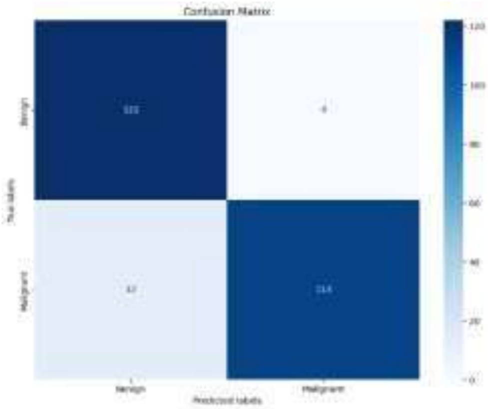

Fig.4. Confusion matrix obtained using InceptionResNetV2.

ii. DenseNet201

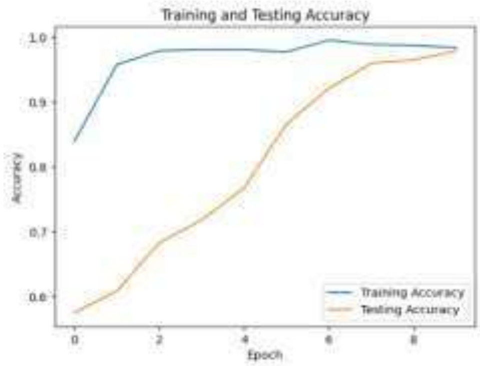

Fig.5. Graph showing the accuracy obtained using DenseNet201.

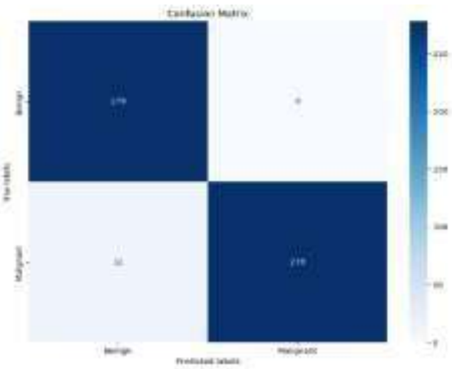

Fig.6. Confusion matrix obtained using DenseNet201.

iii. AlexNet

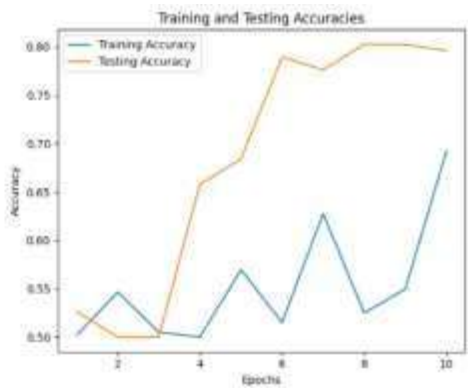

Fig.7. Graph showing the accuracy obtained using AlexNet.

Fig.8. Confusion matrix obtained using AlexNet.

iv. VGG16

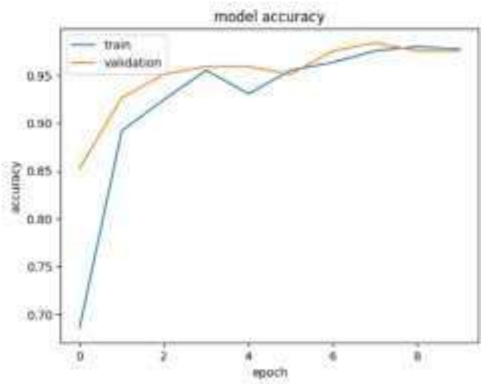

Fig.9. Graph showing the accuracy obtained using VGG16.

Fig.10. Confusion matrix obtained using VGG16.

v. EfficientNetB0

Fig.11. Graph showing the accuracy obtained using EfficientNetB0.

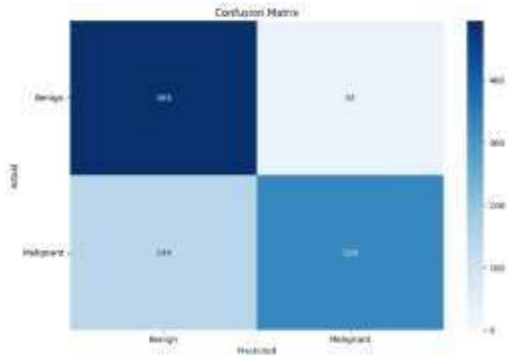

Fig.12. Confusion matrix obtained using EfficientNetB0.

The CNN architectures are trained and tested with the same ocular images dataset where the accuracy graphs of InceptionResNetV2, DenseNet201, AlexNet, VGG16, and EfficientNetB0 are shown in figures Fig.3,5,7,9,11 and the confusion matrices are shown in the figures Fig.4,6,8,10,12 respectively. From the obtained results, it is concluded that InceptionResNetV2, DenseNet, and VGG16 perform better competitively. AlexNet and EfficientNetB0 provide decent results.

3.3. Performance Comparison of different Predictive models for Ocular Melanoma Detection

The CNN architectures that are used for ocular melanoma detection provide good results as shown in Fig.13. InceptionResNetV2, VGG16, and DenseNet201 outperformed other architectures with greater accuracy with slight differences among themselves. The performance metrics such as accuracy, precision, recall, specificity, and F1-score have been plotted into a graph using the values from Table 1.

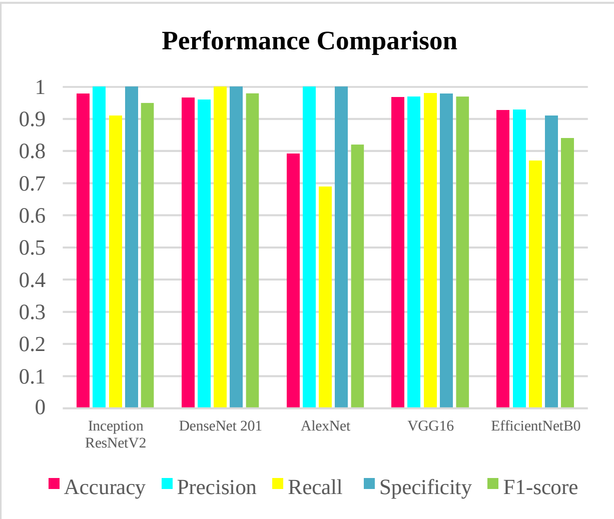

Fig.13. Graph denoting evaluation metrics obtained from various Predictive models for ocular melanoma detection.

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Table 1. Evaluation metrics obtained from various predictive models for ocular melanoma detection.

CNN Architectures	Accuracy	Precision	Recall	Specificity	F1-score
InceptionResNetV2	0.9785	1.00	0.91	1.00	0.95
DenseNet201	0.9668	0.96	1.00	1.00	0.98
AlexNet	0.7921	1.00	0.69	1.00	0.82
VGG16	0.9678	0.97	0.98	0.98	0.97
EfficientNetB0	0.9274	0.93	0.77	0.91	0.84

The performance evaluation metrics of ocular melanoma detection using the CNN architectures is listed in Table 1. It is inferred that InceptionResNetV2, VGG16, and DenseNet201 show higher accuracy in ocular melanoma detection comparatively. These three perform better in the performance metrics with minimal loss.

3.4. Performance Comparison of Proposed System with the Existing System

Table 2. Comparison of evaluation metrics for ocular melanoma detection obtained from various predictive models with the existing system.

CNN Architectures	Accuracy	Recall	Specificity
ANN (Ganguly *et al.*, 2019)	0.85	0.80	0.90
Basic CNN (Ganguly *et al.*, 2019)	0.9176	0.90	0.95
Inception ResNetV2	0.9785	0.91	1.00
DenseNet201	0.9668	1.00	1.00
AlexNet	0.7921	0.69	1.00
VGG16	0.9678	0.98	0.98
EfficientNetB0	0.9274	0.77	0.91

The performance comparison of ocular melanoma detection using the CNN architectures used in the proposed model has been tabulated against the evaluation matrices of existing system architectures as in Table 2. It is inferred that the CNN architectures such as InceptionResNetV2, VGG16, and DenseNet201 are used for ocular melanoma detection outperformed the existing architectures such as ANN, and Basic CNN by providing good results as shown in Fig.14.

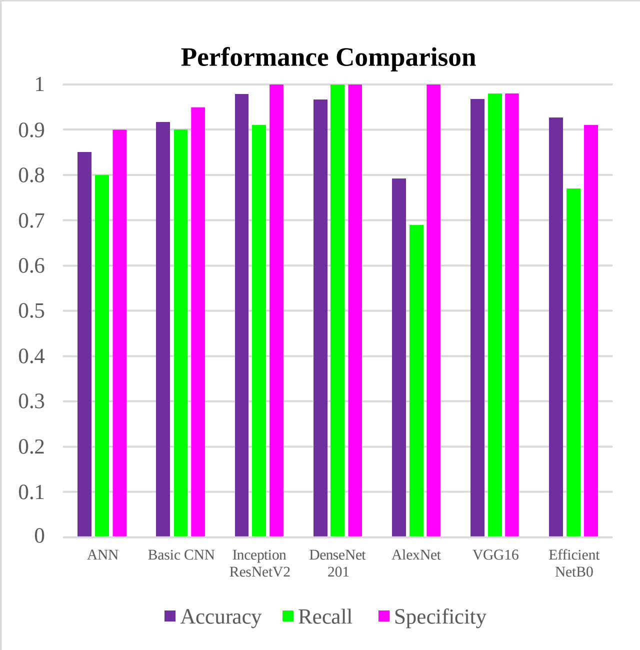

Fig.14. Graph denoting the comparison of evaluation metrics for ocular melanoma of the proposed system with the existing system.

4. Conclusion and Future work

The proposed predictive models mark a significant milestone in the realm of ocular melanoma detection, showcasing the transformative potential of deep learning and artificial intelligence (AI) in revolutionizing melanoma detection processes. Through the integration of various CNN architectures and DL techniques, the developed system has successfully demonstrated its capability to detect ocular melanoma from the input images.

This achievement underscores the power of AI-driven approaches in addressing longstanding challenges in medical diagnosis and disease detection, particularly in the domain of ophthalmology, where the earlier detection of ocular melanoma is tough due to the lack of skilled ophthalmologists. The successful implementation of these CNN models in this paper represents a leap forward in the application of AI technologies to disease detection.

By leveraging the inherent strengths of CNN architectures, such as their ability to capture long-range dependencies and precision, the system excels in generating accurate detection of ocular melanoma. This not only streamlines the detection but also equips healthcare professionals with valuable insights into the diagnostic findings contained within the images, ultimately leading to more informed clinical decision-making, improved patient care outcomes, and early treatment measures.

Thus, this paper would enable ophthalmologists in earlier ocular melanoma detection to provide early and efficient treatment to treat the patients which in turn increases the recovery rate in patients and save their lives. As the field continues to evolve, the integration of AI technologies into medical disease detection practice holds immense promise for improving patient care, driving innovation, and advancing the frontiers of medical science.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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