International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 14 Issue 1, January-2025

Skin Detect: Skin Cancer Detection System

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ABSTRACT

One of the most prevalent malignancies in the world is skin cancer, and successful treatment depends on early detection. In order to detect and categorize skin cancer into melanoma, basal cell carcinoma, and squamous cell carcinoma, this project intends to create an AI-driven system that uses a Convolutional Neural Network (CNN) with the YOLO (You Only Look Once) algorithm. The system uses a dataset of dermoscopic images and the YOLO algorithm for real- time object detection, accurately recognizing and classifying different forms of skin cancer.[1] Techniques for data augmentation and preprocessing are used to increase the model's resilience. The system's promise as a quick, non-invasive diagnostic tool to help medical professionals with early detection is demonstrated by preliminary results. Skin cancer detection and treatment outcomes in clinical settings could be greatly improved with further model validation and improvement. The model goes through extensive data preprocessing and augmentation, including rotation, flipping, and scaling, to produce a more balanced and diversified dataset, improving its generalizability and minimizing class imbalance. This increases dependability across a range of skin tones and lesion kinds. Furthermore, YOLO's real-time detection capabilities enable the device to be used in telemedicine and clinical settings, increasing access to skin cancer screening, particularly in underprivileged areas.

Keywords- Skin Cancer, Convolutional Neural Network, YOLO, Melanoma, Basal Cell Carcinoma, Squamous Cell Carcinoma, Dermoscopic, Data preprocessing, Augmentation and real-time detection.

INTRODUCTION

A rapidly expanding global health concern, skin cancer is made worse by extended exposure to UV light, changes in the environment, and lifestyle choices. Despite their effectiveness, traditional diagnostic techniques are sometimes inaccessible in impoverished areas due to their reliance on intrusive procedures and specialized knowledge. [2] By developing an AI-driven system that provides a quick, non-invasive substitute for early skin cancer screening, this research seeks to close this gap. The system successfully classifies melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) in real time using CNN and YOLO algorithms. Enhancing diagnostic precision, lowering healthcare inequities, and offering a user-friendly tool for clinical and telemedicine applications that balance human agility with mechanical strength are the objectives.

Problem Statement

The need for effective and scalable diagnostic tools is highlighted by the rising incidence of skin cancer worldwide, especially in areas with poor access to medical care. Traditional approaches have drawbacks like invasiveness from their reliance on biopsies and histopathology, reliance on specialists because dermatologists and diagnostic equipment are scarce in rural areas, and delayed diagnosis from late-stage detection because of low awareness and accessibility. By developing an AI-based system that can diagnose skin cancer in real time without intrusive procedures and making it available online, this research seeks to overcome these obstacles.

Scope and Relevance

The goal of this research is to use artificial intelligence to create a real-time, non-invasive method of detecting skin cancer. [7] Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are the three main forms of skin cancer that the system targets in order to provide precise categorization through the use of sophisticated image processing algorithms. The system is appropriate for clinical and telemedicine applications because of its high precision and efficiency, which are ensured by the integration of CNN for classification and detection. By providing a scalable and affordable diagnostic tool, this AI-driven system has the potential to democratize access to healthcare, particularly in underprivileged areas with limited access to specialists.

Relevance encompasses several facets of medical technology and healthcare. [3] Globally, the incidence of skin cancer is on the rise, and conventional diagnostic techniques can include invasive procedures, expensive, and delayed results. By offering a web-based platform that lets users upload photos and get real-time diagnostic feedback, this project tackles these issues. By enabling prompt responses, such a system could improve patient outcomes, lessen the strain on healthcare systems, and improve early detection. [4] Additionally, this invention contributes to the continuous development of AI in medicine and is in line with the global movement toward easily available, technologically advanced healthcare solutions.

Objectives

The primary objective of this project is to develop an advanced deep learning system that combines YOLO for real-time lesion detection with a CNN for precise classification of skin cancer types. By leveraging the strengths of these models, the system aims to provide accurate, efficient, and automated diagnostic capabilities. A key focus is on designing an intuitive web interface that allows users to upload dermoscopic images for immediate analysis, ensuring a seamless and accessible user experience. The project also emphasizes rigorous data preprocessing and augmentation to enhance the model's robustness and accuracy across diverse scenarios.

Beyond the technical goals, the project strives to democratize access to early skin cancer detection by offering a cost-effective, scalable solution, particularly beneficial for regions with limited medical resources.[4] It seeks to contribute to medical AI research by demonstrating the potential of integrating YOLO and CNN for healthcare diagnostics. This innovative approach not only showcases the efficacy of these technologies but also sets a precedent for their application in other areas of medical imaging and diagnostics.

Ultimately, the system is designed to support healthcare providers by delivering accurate and timely diagnosis. By reducing reliance on invasive diagnostic methods, the solution can improve patient outcomes and streamline clinical workflows. [5] This holistic approach addresses the need for accessible, non-invasive, and efficient diagnostic tools, significantly advancing early detection efforts in skin cancer care.

METHODOLOGY

In order to ensure a wide range of lesion kinds, image quality, and presentations for training a robust model, a diversified dataset of 995 dermoscopic images was collected from platforms such as Kaggle. To guarantee uniform input for the models, preprocessing operations involved scaling the photos to uniform dimensions, such as 416x416 or 224x224 pixels. Gaussian filters were used for noise reduction in order to remove unimportant changes, and histogram equalization was used for contrast enhancement in order to make lesions more visible, particularly in difficult lighting situations.

Data augmentation techniques like rotation, flipping, brightness adjustment, and noise addition were used to improve the model's robustness and help it generalize more effectively across a range of lesion appearances and imaging settings. The design integrated CNN for in-depth classification and YOLO for real-time lesion detection. While CNN categorized the lesions into groups like melanoma, basal cell carcinoma (BCC), or squamous cell carcinoma (SCC), YOLO located the lesions by locating regions of interest in the photos. [12] Hyperparameters like learning rate and batch size were tuned for better performance, and validation datasets guaranteed model accuracy and reduced overfitting. In the end, an intuitive online interface was created that enables users to upload photographs and get real-time diagnostic results from the AI algorithms in the backend.

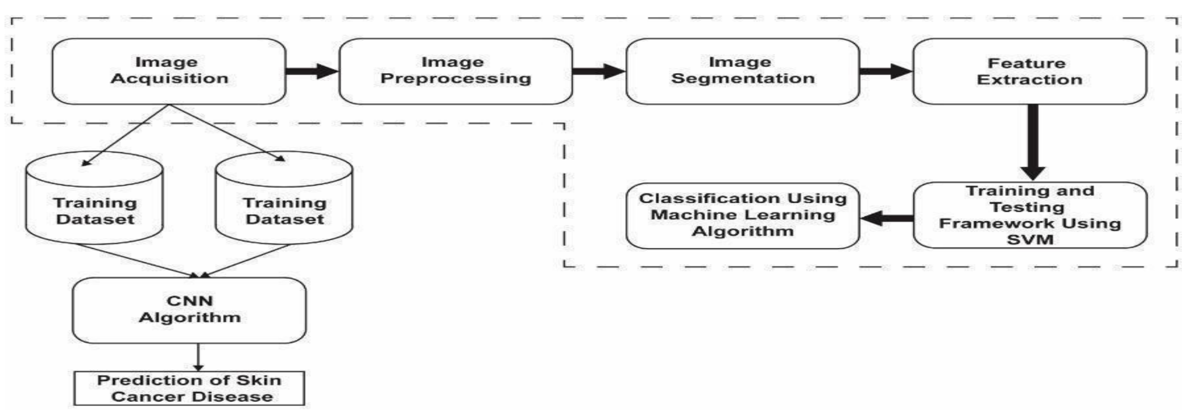

Fig 1: Skin Cancer Detection System

Software Requirements

This project builds a complete skin cancer detection system using Python 3.9.13 and Vision Studio Code. The main features of Visual Studio Code, such IntelliSense and Git integration, simplify development by offering effective version management and insightful code recommendations. Git makes code management and collaboration simple, and IntelliSense boosts efficiency with automated imports and code autocompletion. These resources work together to make coding easy and effective.

Python 3.9.13, the framework on which the project is built, comes with well-known machine learning libraries. Scikit-learn handles traditional machine learning tasks, while TensorFlow, Keras, and PyTorch assist the creation of deep learning models. For data management and preprocessing, libraries like Pandas and NumPy are essential, while OpenCV and PIL provide powerful image processing and augmentation features. [5] Analysis of training data and metrics is made possible by visualization tools like Matplotlib and Seaborn, which guarantee unambiguous insights into model performance. The system combines unique CNNs for classification tasks with pre-trained CNNs such as ResNet and VGG. These models evaluate uploaded photos of skin lesions to determine whether they are benign or cancerous. Using streamlit, the frontend complements the backend and offers an easy-to-use interface for uploading images and displaying results. The machine learning models and the frontend are seamlessly connected via the backend, allowing for real-time predictions and the presentation of findings to users in an understandable and educational way.

RESULT

Training and Validation Performance of CNN Model:

The performance evaluation of the skin cancer classification model is crucial in determining its effectiveness. The training and validation accuracy trends, as shown in Figure 2, indicate that the model learns progressively over epochs. Initially, the accuracy increases rapidly, demonstrating effective learning. Both training and validation accuracy stabilize around 85%, with minimal deviation, suggesting that the model generalizes well to unseen data. The close alignment of these curves confirms that overfitting is minimal, which is a crucial factor in ensuring reliable predictions on test data. Similarly, the training and validation loss curves exhibit a steady decline over epochs, indicating efficient learning and convergence. At the beginning of training, the loss values are high, but they decrease significantly as the model refines its parameters. The validation loss follows a similar pattern to the training loss, implying that the model is not overfitting to the training set. [6] The absence of drastic fluctuations in the loss curves suggests that the model's hyperparameters, such as learning rate and batch size, were well-optimized, allowing for smooth training progression.

The consistency between accuracy and loss trends confirms that the model effectively distinguishes between melanoma, basal cell carcinoma, and squamous cell carcinoma. However, further enhancements, such as data augmentation, hyperparameter tuning, and regularization techniques, could improve generalization further. Techniques like dropout layers or L2 regularization may help in reducing any potential overfitting in future iterations. Additionally, increasing dataset diversity by incorporating more varied skin cancer images can enhance model robustness. The CNN model shows strong classification with minimal overfitting, effective learning, and optimization.

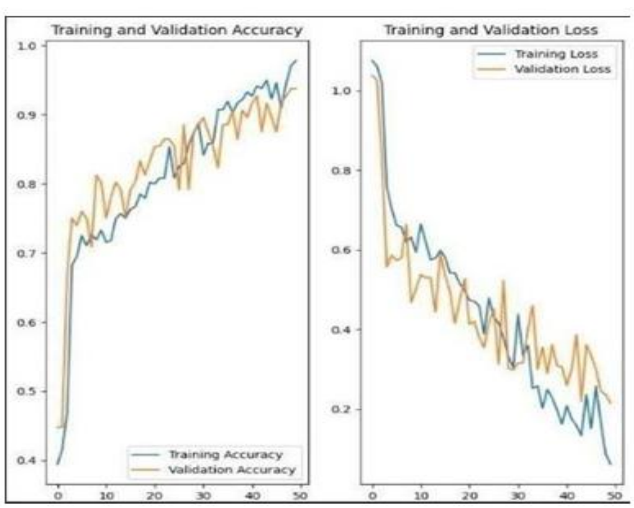

Fig 2: Accuracy and Loss Metrics of CNN Model

The confusion matrix, as shown in Figure 3, provides an in-depth evaluation of the skin cancer classification and model's performance in 3 categories: basal cell carcinoma, melanoma, and squamous cell carcinoma. The diagonal values represent correctly classified instances, while off- diagonal values indicate misclassified cases. The model demonstrates high classification accuracy, with 42 correct predictions for basal cell carcinoma, 55 for melanoma, and 23 for squamous cell carcinoma. However, there are misclassifications, including 3 squamous cell carcinoma cases wrongly classified as basal cell carcinoma, 2 melanoma cases as basal cell carcinoma, and 3 basal cell carcinoma cases misclassified as either melanoma or squamous cell carcinoma. Among the three classes, melanoma shows the highest accuracy with minimal misclassification, suggesting that its distinguishing features are well-learned by the model.

In contrast, squamous cell carcinoma exhibits more confusion with basal cell carcinoma. The presence of these misclassifications suggests that further enhancements are necessary, such as improving data preprocessing, applying data augmentation techniques, fine- tuning hyperparameters, or using advanced architectures like ensemble models or transfer learning.These techniques make the architecture more complex. Additionally, incorporating a larger and more diverse dataset could improve the model's robustness and its ability to differentiate between similar looking skin cancer types. Further refinements could enhance its real-world applicability in medical image classification.

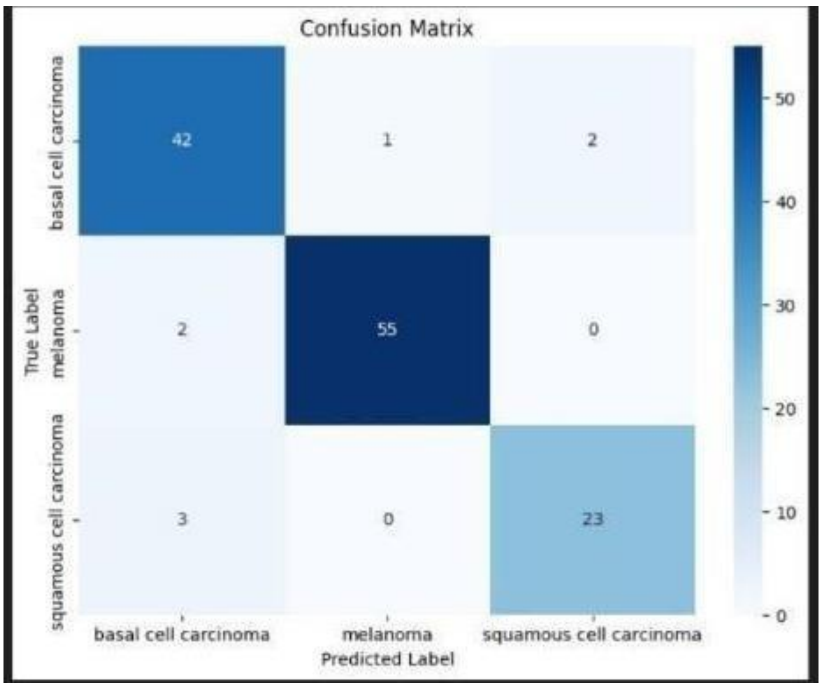

Fig 3: Confusion Matrix of CNN Model

Training and Validation Performance of YOLO Model:

The YOLO model's training and validation results indicate the overall performance of the model in classifying skin cancer types. The training and validation loss curves show a steady decline, indicating effective learning during the training process. Initially, both losses are high, but they decrease as the model optimizes its weights, demonstrating convergence. The validation loss follows a similar trend, confirming that the model generalizes well to unseen data without significant overfitting.

The accuracy matrix further supports the model's efficiency. The top-1 accuracy graph shows a sharp increase, reaching above 0.9, which means the model is correctly classifying most cases. The top-5 accuracy remains stable at nearly 1.0, suggesting that the correct class is almost always within the top predictions. This is crucial for medical applications, where a high-confidence classification is essential.

Additionally, the model's inference results indicate a successful classification of a sample image, with a confidence score of 1.00 for squamous cell carcinoma. The processing speed metrics 307.5ms for preprocessing and 97.0ms for inference suggest that the YOLO model is efficient in real-time detection, making it suitable for clinical or diagnostic applications. Overall, these results demonstrate that the YOLO-based model is well-trained, exhibits high accuracy, and performs efficiently in detecting and classifying skin cancer types.

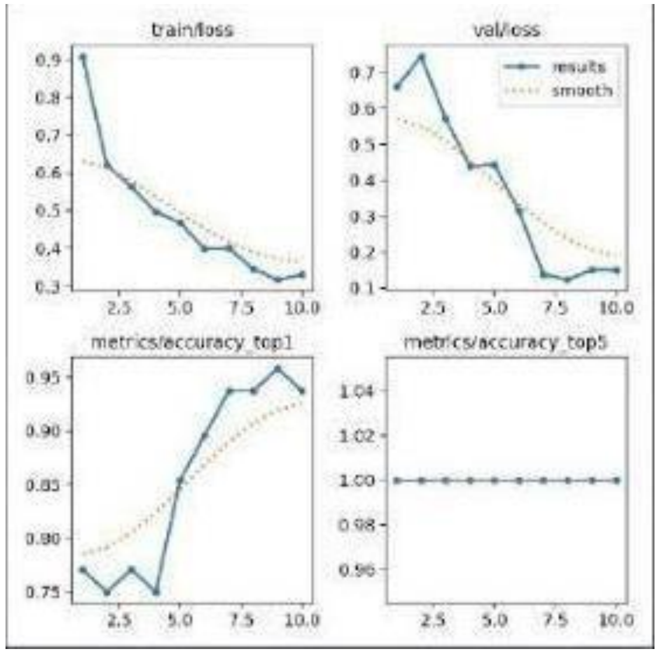

Fig 4: Accuracy and Loss Metrics of YOLO Model

The confusion matrix displayed in the image represents the performance of the YOLO model in classifying different types of skin cancer, including basal cell carcinoma, squamous cell carcinoma, and melanoma. The matrix provides insights into the model's classification accuracy by comparing predicted labels with true labels. Darker blue shades indicate higher counts, representing strong agreement between predicted and actual labels. The diagonal elements show the correctly classified instances for each category, while off-diagonal elements represent misclassifications. [8] A higher number of correctly classified cases along the diagonal signifies that the model is performing well in distinguishing between different skin cancer types, with minimal misclassification.

From the confusion matrix, it is evident that the model has successfully classified most instances with high accuracy, as indicated by the strong diagonal values. However, some minor misclassifications are present, suggesting that further improvements, such as data augmentation, hyperparameter tuning, or increasing dataset size, may enhance performance. [10] The confidence score of 0.97 for basal cell carcinoma detection further supports the reliability of the model. This analysis highlights the potential of the YOLO model in automated skin cancer classification, demonstrating its ability to provide accurate predictions, which is crucial for early detection and diagnosis in medical applications.

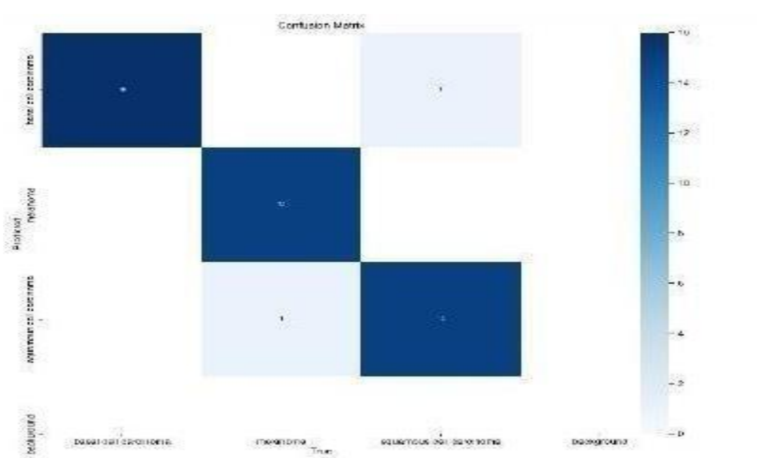

Fig 5: Confusion Matrix of YOLO Model

Comparative Study CNN vs YOLO:

Parameter	CNN	YOLO
Accuracy	93.8%	96.9%
Loss	32%	31%
F1 Score	93.9%	96.8%
Recall	93.8%	96.8%
Precision	94.1%	98.4%
Specificity	96.8%	98.8%

CONCLUSION

The Skin detect: Deep Learning-Based Skin Cancer Detection System offers a revolutionary method of skin health management. [9]The implementation of YOLO and CNN algorithms for skin cancer detection has demonstrated significant potential in accurately classifying melanoma, basal cell carcinoma, and squamous cell carcinoma. The comparative analysis between these models highlights YOLO's superior detection capability, achieving higher accuracy with lower computational cost and faster inference time, making it more suitable for real-time applications. CNN, while effective, requires more epochs to converge and exhibits higher misclassification rates due to overfitting and complex feature extraction processes. Misclassification remains a critical challenge, primarily arising from inter-class similarities in lesion characteristics, variations in lighting conditions, and dataset imbalances, which can be mitigated through advanced augmentation techniques and improved training methodologies.

This research underscores the importance of deep-learning models in medical imaging, offering a promising approach for early skin cancer detection. Integrating the model into a web-based interface enhances accessibility, allowing for preliminary screening and assisting dermatologists in clinical decision-making. Future work can focus on optimizing model architectures, incorporating attention mechanisms, and utilizing larger, more diverse datasets to further improve classification accuracy. Additionally, explainable AI techniques can be explored to enhance model interpretability, ensuring reliability and trustworthiness in real-world medical applications. [11] This study contributes to the advancement of AI-driven dermatological diagnostics, bridging the gap between research and practical implementation. It offers dependable and easily accessible assistance by utilizing mobile applications and sophisticated machine learning algorithms. The system has the potential to improve accessibility and overall health care, benefiting both individual users and healthcare providers.

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