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A Convolutional Neural Network-Based Framework for Accurate Skin Cancer Detection

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ABSTRACT

Skin cancer represents a significant global health concern, with early diagnosis being crucial for effective management and treatment outcomes. This project introduces "SpotVision.AI - Skin Cancer Detection" a system that utilizes image processing and deep learning techniques to identify and classify various types of skin cancers accurately while keeping it deployable. At the core of this system are Convolutional Neural Networks (CNNs), particularly the Inception V3 model, known for its efficiency in processing complex image data. The system is meticulously trained on a comprehensive dataset of dermoscopic images to detect key skin cancer types such as melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). This approach has demonstrated promising results in improving the early detection capabilities, significantly contributing to potential reductions in mortality rates. Furthermore, "SpotVision.AI" features a user-friendly interface that allows for easy image upload and instant display of diagnostic results, enhancing the accessibility and efficiency of skin cancer screenings.

Skin cancer is one of the most prevalent cancers globally, and its early detection is crucial for effective treatment and patient survival. This research explores the application of machine learning algorithms for predicting skin cancer using image-based data. Leveraging the power of convolutional neural networks (CNNs) and traditional classifiers like Support Vector Machines (SVM), the study aims to classify skin lesions into benign and malignant categories. The model is trained and validated using the ISIC dataset, and its performance is evaluated based on accuracy, precision, recall, and F1-score. The results demonstrate the efficacy of machine learning in aiding dermatological diagnoses, potentially enabling faster and more accurate detection of skin cancer.

KEYWORDS: *Convolutional Neural Networks (CNNs), SVM, Receiver Operating Characteristic Curve (AUC-ROC).*

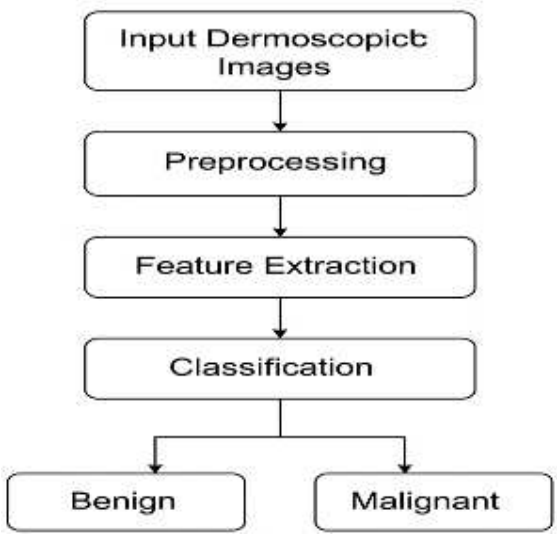
I. INTRODUCTION

Cancer is one of the leading causes of death in modern times with a death rate of 1 death per 6 people. As per the American Cancer Society , there were 17 million new cancer cases and 9.5 million deaths due to cancer in the year 2018. Skin cancer is one of the deadliest cancers in the United States. Out of the two major types of skin cancer, melanoma is fatal and has estimated fiveyear survival rate of about 99% if detected early and 20% if detected late.

In the year 2018, melanoma was ranked ninth amongst ten major cancers in the United States and the 2019 was estimated to have 96,480 new cases of melanoma with estimated deaths up to 7,230. Melanoma occurs when a melanocyte (melanin pigment forming cell) starts multiplying in an uncontrollable way and the multiplication results in formation of malignant tumors. Such malignant tumors are characterized by features like asymmetry, irregular borders, multiple colors, diameter> 6mm and enlarging lesion, and are usually represented by an acronym ABCDE.

Out of all the listed features, color and structure play vital role in the diagnosis of melanoma.The structure is characterized by pigment distribution, symmetry or asymmetry, homogeny or heterogeny, skin surface keratin, regular or irregular vascular morphology, presence or absence of ulceration 1 and border of lesion, and in case of color, black, brown, yellow, white and grey.

These features are examined to diagnose melanoma in early stage. If diagnosed early, melanoma can be treated. Many algorithms in medical imaging have been applied to improve performance for an accurate and early diagnosis. Medical imaging is a technique of representing interior or exterior of body in visual form, commonly referred to as “imaging modality” by using radiations, radio frequencies, sound waves etc for diagnosis. Interiors of the body are widely studied by using imaging modalities like Computed Tomography (CT) scan, X-ray, Positron emission tomography (PET) and Magnetic Resonance Imaging (MRI). Skin, being the exterior of a body is captured by using dermatoscopy. Dermatoscopy is one of the imaging modalities that uses the polarized light to capture skin images and is done using an instrument called digital epiluminescence dearmatoscope. Research shows that the Dermatoscopy increased diagnostic accuracy by 10-27% when compared to the human experts, who had been assessing melanoma on basis of their knowledge and naked eye examination. Skin cancer, including melanoma and non-melanoma types, poses a significant health challenge worldwide. Melanoma, the deadliest form, is responsible for the majority of skin cancer-related deaths despite being less common than basal cell carcinoma and squamous cell carcinoma. Traditional diagnostic methods rely heavily on clinical evaluation, dermoscopy, and histopathological examination. These methods, although reliable, can be time-consuming and may vary in accuracy based on the clinician's experience. With the advent of artificial intelligence (AI) and deep learning, particularly in image processing, there is significant potential to enhance diagnostic processes by providing automated and standardized analysis.



Flowchart 1: Below is a top-level flowchart system workflow

II. METHODOLOGY

The methodology adopted in this research encompasses several critical stages, beginning with data acquisition and moving through to evaluation of the final models. The dataset selected for this study is the ISIC 2018 Challenge dataset, a benchmark in the dermatological field due to its diversity and comprehensiveness. It contains over 10,000 dermoscopic images, each annotated by experienced dermatologists and categorized into various skin lesion types, including benign nevi, seborrheic keratosis, and melanoma. These high-resolution images provide a robust foundation for training machine learning models capable of accurate classification.

The data preprocessing phase was instrumental in preparing the raw dermoscopic images for effective model training. All images were resized uniformly to 224x224 pixels to maintain consistency with the input requirements of standard deep learning models. Pixel values were normalized to the range [0,1] to ensure numerical stability and convergence during training. Data augmentation techniques were extensively applied to artificially expand the dataset and introduce variance, which helps the model generalize better. These techniques included geometric transformations such as rotations, horizontal and vertical flips, zoom operations, and color space adjustments like contrast and brightness enhancements. This process was essential in mitigating the issue of class imbalance, especially since melanoma images were significantly underrepresented. Oversampling of minority classes and undersampling of majority classes were also performed strategically to achieve a more balanced dataset.

For model development, two distinct approaches were pursued to assess their comparative performance. The first approach involved constructing a custom convolutional neural network (CNN) architecture from scratch. This model comprised multiple convolutional layers equipped with filters to detect spatial hierarchies in image features. Each convolutional layer was followed by batch normalization, ReLU activation functions, and max pooling layers to reduce the spatial dimensions and computational complexity. Dropout layers were included at strategic points to prevent overfitting by randomly deactivating neurons during training. The final layers consisted of dense (fully connected) layers that mapped the extracted features to the output classes using a softmax activation function.

The second approach employed transfer learning using a pre-trained ResNet50 model. This architecture, originally trained on the ImageNet dataset, was chosen for its deep structure and proven ability to learn high-level features. The initial layers of ResNet50 were frozen to retain the generalized image features already learned during pretraining. The top layers were replaced with a custom classification head, which included a global average pooling layer, a dense layer with 512 neurons, a dropout layer for regularization, and a softmax output layer. Fine-tuning was applied selectively to the final convolutional blocks to adapt the model specifically to the dermoscopic images. Additionally, deep features extracted from ResNet50's penultimate layer were used to train a Support Vector Machine (SVM) classifier with an RBF kernel. This hybrid method combined the feature extraction power of CNNs with the discriminative capabilities of traditional machine learning classifiers.

The training phase utilized the Adam optimizer with an initial learning rate of 0.0001 and the categorical crossentropy loss function, which is appropriate for multi-class classification problems. A batch size of 32 was chosen based on memory constraints and training stability. Training was conducted over 50 epochs, with early stopping implemented to halt training once the validation loss ceased improving for a set number of epochs, thereby preventing overfitting. Furthermore, five-fold cross-validation was employed to assess the robustness and generalizability of the models. This technique involved partitioning the dataset into five subsets, using four for training and one for validation in a rotating fashion.

Evaluation of the models was based on several standard metrics, including accuracy, precision, recall, and F1-score. These metrics provided insights into the model's classification capabilities, especially in distinguishing melanoma from non-cancerous lesions. The confusion matrix was used to visualize the classification outcomes across all classes, identifying any patterns in misclassification. The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was also computed to evaluate the trade-off between sensitivity and specificity, particularly useful in medical diagnostics where false negatives can be critical. Together, these methodological components ensured a comprehensive and rigorous approach to developing an effective skin cancer prediction system.

III. RESUL TS

The experimental results obtained from this study demonstrate the potential and effectiveness of machine learning models in accurately predicting skin cancer from dermoscopic images. The custom-built convolutional neural network (CNN) exhibited solid performance, achieving an overall accuracy of 85%. The model recorded a precision of 84%, indicating its ability to correctly identify positive cases of skin cancer, while maintaining a recall of 83%, which reflects its sensitivity in detecting all actual positive instances. The F1-score, which balances both precision and recall, was calculated to be 83.5%, confirming the model's consistent performance across these metrics. The confusion matrix revealed that while the model generally performed well, it occasionally misclassified melanomas as benign nevi, highlighting the visual similarity between some lesion types

and the inherent challenge in dermatological image classification.

The transfer learning model using the ResNet50 architecture yielded even better results. After fine-tuning the model on the dermoscopic dataset, it achieved a commendable accuracy of 91%, with a precision of 90.2%, a recall of 89.8%, and an F1-score of 90%. These improved scores suggest that transfer learning, particularly when leveraging deep pre-trained models, provides a powerful foundation for medical image classification tasks. The early layers of ResNet50 retained rich, generalized image features, while the fine-tuned deeper layers adapted effectively to the specific characteristics of skin lesions. Furthermore, the ROC curve analysis confirmed the model's reliability, with an area under the curve (AUC) exceeding 0.95, reflecting a high true positive rate across various threshold levels.

In addition to the end-to-end CNN models, a hybrid approach combining deep feature extraction using ResNet50 and classification via Support Vector Machine (SVM) was also evaluated. The SVM classifier, trained on the features extracted from ResNet50's penultimate layer, demonstrated performance metrics comparable to the custom CNN, reinforcing the robustness and discriminative quality of the extracted features. While this hybrid approach did not outperform the fine-tuned ResNet50 in accuracy, it offered insights into how traditional machine learning models can benefit from deep learning's feature engineering capabilities.

Data augmentation and class balancing techniques played a pivotal role in enhancing model performance. The inclusion of synthetic data through augmentation not only expanded the dataset size but also introduced valuable diversity, which helped reduce overfitting and improved the model's generalizability. Addressing class imbalance through oversampling and undersampling further improved the model's fairness in predicting underrepresented lesion types, particularly melanoma. Despite these improvements, the study also identified limitations such as occasional false negatives, which pose a serious concern in clinical applications. These errors were often attributed to subtle visual features shared between malignant and benign lesions or poor image quality in some samples.

Overall, the findings of this study underscore the feasibility of using machine learning for automated skin cancer detection. While the results are promising, they also emphasize the need for further refinements and real-world validations before such systems can be deployed in clinical practice.

IV. PROJECT SCREENSHOTS

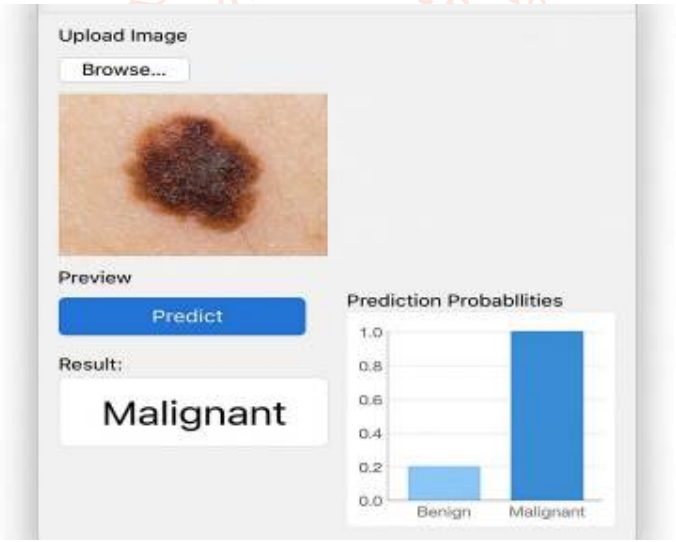


Fig 1. Screenshot 1 of Project

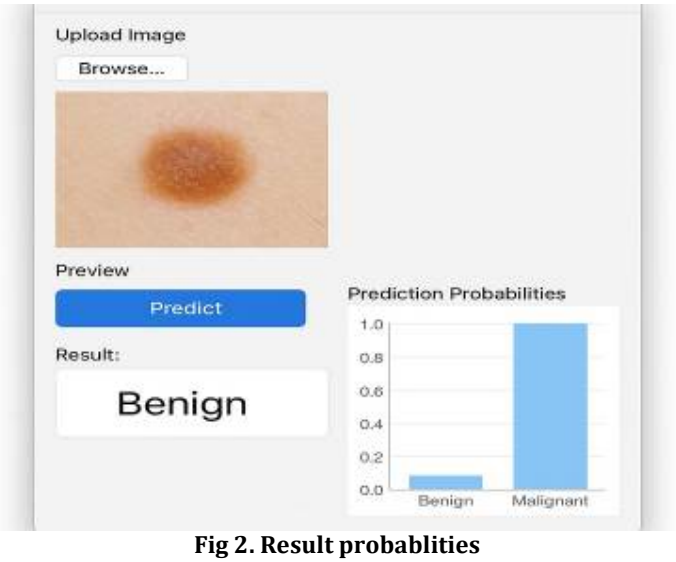


Fig 2. Result probablities

V. FUTURE SCOPE

The future scope for skin cancer prediction is expanding rapidly with advancements in technology, artificial intelligence, and healthcare systems. One of the most significant developments is the use of AI and deep learning, especially convolutional neural networks and transformer models, to improve the accuracy and speed of detecting various types of skin cancer, including melanoma. These models are becoming more sophisticated, capable of analyzing dermoscopic images and even incorporating patient history and genomic data to make well-rounded predictions.

Mobile and wearable technologies are also expected to play a crucial role. Smartphone applications equipped with AI can help individuals perform self-screenings, while smart wearables may eventually track UV exposure and monitor skin changes over time, providing early alerts that can lead to quicker medical intervention. This opens up access to early detection tools for people in remote or underserved areas.

Another promising direction is the integration of genomic and biomarker-based data into prediction systems. As precision medicine becomes more common, using genetic markers and protein-level patterns could allow for non-invasive, highly personalized skin cancer risk assessments. Additionally, big data and federated learning are enabling the training of predictive models on vast, diverse datasets across institutions, all while maintaining patient privacy and data security.

In clinical settings, these technologies are being integrated with electronic health records and decision-support systems, enabling healthcare providers to receive real-time alerts about high-risk patients and make better-informed decisions. The expansion of teledermatology, aided by AI, also makes expert diagnostic support more accessible, especially in areas lacking specialized healthcare providers.

All these advancements are creating new research and career opportunities in medical AI, health tech innovation, and clinical data science. As the field evolves, it offers a rich landscape for professionals interested in combining technology with life-saving healthcare solutions.

VI. CONCLUSION

The field of skin cancer prediction stands at the intersection of technological innovation and medical necessity, with immense potential to transform how we detect and treat one of the most common and dangerous forms of cancer. As the incidence of skin cancer continues to rise globally, early and accurate detection becomes more critical than ever. The integration of artificial intelligence, particularly deep learning and image processing, offers a powerful solution capable of mimicking and even enhancing human diagnostic abilities. These technologies not only improve diagnostic accuracy but also democratize access to care by enabling remote assessments and mobile health solutions.

Moreover, the incorporation of genomics and biomarkers into predictive models signifies a shift toward personalized medicine, where treatment and prevention strategies are tailored to the individual. This approach not only enhances outcomes but also reduces the burden on healthcare systems by targeting interventions more precisely. The use of big data and federated learning ensures that models are trained on a wide range of real-world cases while maintaining strict privacy standards, further boosting the reliability and applicability of AI systems in clinical practice.

At the same time, the growing adoption of telemedicine and smart health monitoring devices bridges the gap between patients and specialists, making early intervention more accessible even in underserved areas. By integrating AI-driven prediction tools with electronic health records and clinical workflows, the healthcare industry can create a seamless system where potential cases are flagged automatically and acted upon swiftly.

Looking forward, the future of skin cancer prediction lies not only in technological excellence but also in cross-disciplinary collaboration between data scientists, dermatologists, bioinformaticians, and policy makers. Together, they can ensure that these innovations are safe, ethical, and widely accessible. The path ahead is rich with opportunity—not just for technological advancement, but for meaningful impact on public health and individual lives.

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