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Hybrid Features for the Identification and Categorization of Skin Cancer

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Abstract: - The halal food control system is one of the critical aspects that need attention in sustaining the Malaysian halal industry. In practice, the existing halal food control system involves the roles of several stakeholders and is implemented independently according to their respective jurisdictions. No integrated control mechanism coordinates the roles of all stakeholders, thus resulting in fraud cases to easily happen in the industry. To effectively coordinate these roles, an integrated halal food control system must be developed. Therefore, this concept paper aims to discuss the roles of stakeholders involved in the halal food control system and to propose a conceptual halal food stakeholder control system model based on the objectives of the Islamic law framework. Information for this paper is gathered based on a literature review of previous studies related to the halal food control system. The conceptual model is expected to be a reference and guideline for all stakeholders involved and will serve as a theoretical foundation for future research in this area. Additionally, it can enhance consumer trust in Malaysia's halal certification and support the country's goal of becoming a leader in the global halal food industry.

Keywords: Skin cancer detection and classification (SCDC-Net), computer-aided diagnosis (CAD), Generative Adversarial Network, Hybrid U-Net (HU-Net), Discrete Wavelet Transform (DWT), Grey-level Co-Occurrence Matrix (GLCM).

I. INTRODUCTION

Over the years, there has been an exponential increase in the incidence of cancer cases. An abnormal development of skin cells is called skin cancer. It is commonest forms of cancer and is further divided into non-melanoma and melanoma varieties. Despite being less frequent than other forms of skin cancer, melanoma can be deadly if left untreated. However, it is not the only kind of skin cancer that requires care. It becomes necessary to promptly identify and classify the skin cancer for the recovery of the patient. Image-based computer aided diagnosis (CAD) have high capability for early detection of malignant type of skin cancer. We are aiming to develop a model that would accurately detect skin cancer.

A. Problem Statement

The user interface is a critical point of engagement in the modern Skin Cancer Detection and Classification System, providing users with a seamless experience while looking for quick and accurate information regarding skin lesions. Users upload photographs of skin lesions using the user-friendly interface to start the procedure, which then proceeds through the following phases in an advanced but approachable manner: The submitted image is carefully preprocessed using the UG-Net model, which combines generative adversarial networks (GAN) with U-Net to great effect. By removing hair interference, a frequent problem in skin lesion photos, this procedure guarantees a high-quality input for further analysis. Subsequently, segmentation operations are carried out by the Hybrid U-Net (HU-Net) to highlight and identify the important features inside the skin lesion. This identifies the regions of interest, improving the accuracy of the next study. Next, features are retrieved using the DWT and GLCM. Together, GLCM and DWT provide a comprehensive set of features necessary for precise categorization, with GLCM capturing textural patterns and DWT providing frequency information. Following feature extraction, the deep Q neural network (DQNN) model is fed the data. This model has already been trained to identify patterns that indicate either non-melanoma or melanoma skin malignancies. The classification output of the model appears quickly on the user interface, giving users. The user is provided the final outcome, including the presence or absence of cancer. The user interface presents cancer information, whether it is melanoma or not, in an understandable and straightforward manner.

B. Existing System

- Limited feature analysis: Existing systems often rely on basic feature extraction techniques, leading to inaccuracies in distinguishing cancerous and non-cancerous lesions.
- Hair occlusion: Hair on skin lesions can obscure crucial features, making diagnosis difficult. Existing systems might not have effective methods to address this issue.

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- Segmentation inaccuracies: Precise lesion segmentation is critical for accurate feature extraction and classification.
- Existing systems might have limitations in accurately segmenting lesions from surrounding skin.
- Single-level feature extraction: Relying solely on basic features like color and texture may not capture the full complexity of skin lesions. Existing systems might lack diverse feature extraction techniques.

C. Proposed System

- Transfer learning for robust feature extraction: By leveraging pre-trained models and advanced networks like UG-Net
- Hair removal for improved diagnosis: UG-Net combines U-Net's segmentation capabilities with GAN's hair removal and HU-Net, SCDC-Net can extract more robust and informative features from skin lesions, leading to more accurate classification. abilities, effectively eliminating hair-induced occlusion and providing a clearer view of the lesion for accurate analysis.
- Hybrid U-Net for precise segmentation: HU-Net architecture refines the segmentation process, further isolating the lesion from surrounding skin and ensuring better feature extraction for accurate classification.
- Multi-level feature extraction for enriched data: SCDC-Net utilizes both DWT and GLCM techniques to capture a wider range of features from different textures and patterns within the lesion, providing the DQNN model with a richer data set for enhanced classification accuracy.

II. LITERATURE REVIEW

[1] The methodology proposed in this paper combines transfer learning convolutional neural network (TL-CNN) for classification based on transfer learning for segmentation. The approach entails segmentation using the PMDN technique after preprocessing with and a convolutional autoencoder and decoder (CAED). After that, the segmented region's features are extracted using the TL-CNN, which is then utilized to categorize the various forms of skin cancer. Compared to traditional approaches, this method performs better in segmentation, feature selection, and classification. [2] In the context of skin cancer classification, this research proposes the integration of hybrid convolutional neural networks (CNNs) with an SVM classifier. The study introduces two novel hybrid CNN models, incorporating an SVM classifier at the output layer. These models exhibit superior performance compared to conventional CNNs, boasting accuracy rates of 88.02% and 87.43% on the ISBI 2016 dataset, respectively. The methodology involves the extraction of features from dermoscopy images using two CNN models, followed by concatenation before input into the SVM classifier. Notably, this approach addresses issues such as inter-operator variability, leading to enhanced classification accuracy for dermoscopy images. The integration of CNNs and SVMs emerges as a promising strategy for advancing the effectiveness of skin cancer classification methodologies.

[3] The study proposes the utilization of updated InceptionV3 and VGG16 models for the categorization of skin cancer, implementing a preprocessing step to resize and augment the quantity of photos in the seborrheic keratosis and melanoma classes. Notably, the updated VGG16 model demonstrated superior performance, surpassing previous modern techniques with an impressive accuracy of 73.33% in melanoma classification. Regarding the modified InceptionV3 model, it achieved an 84% accuracy in classifying the 'Nevus' category, while the modified VGG16 model exhibited a performance of 54%. However, both models exhibited lower accuracy in the "Seborrheic keratosis" class. Despite these disparities, the suggested approach, relying on the modified VGG16 model, holds promise in enhancing melanoma classification accuracy compared to prior methodologies. The updated InceptionV3 model excelled in the "Nevus" class but demonstrated diminished accuracy in the "Seborrheic keratosis" class. [4] The study employed deep transfer learning models to construct a classification system which can perform categorizing skin images into seven distinct classes, utilizing the HAM1000 dataset of dermoscopy images as input. In evaluating the system, several advantages and shortcomings were identified. Despite achieving a commendable overall accuracy of 82.9%, certain challenges were noted, including dataset imbalance, a scarcity of images in specific categories, and the complexity introduced by a large number of classes. The study meticulously compared its findings with related literature, shedding light on the performance evaluation results of the employed models. However, the provided sources did not explicitly outline the study's conclusion, leaving room for further exploration.

[5] The proposed methodology encompasses several essential steps within the realm of image processing. These include segmentation, the extraction of texture features, and comprehensive picture preprocessing. Subsequently, an ANN algorithm is deployed for the purpose of classification. The main goal of this technological approach is to improve the accuracy of skin cancer diagnosis when compared to prevailing methods. Leveraging the proven efficacy of artificial neural networks in cancer diagnosis adds a layer of reliability to the strategy. Moreover, the incorporation of hybrid texture features serves as an additional advantage, contributing to an improved classification accuracy. This multifaceted approach combines sophisticated image processing techniques with advanced classification algorithms, demonstrating a concerted effort to elevate the standards of skin cancer diagnosis.

[6] The study employs deep learning methodologies, likely involving Convolutional Neural Networks (CNNs) or similar architectures, to discern skin lesions and detect cancer through the training of deep neural networks on a dataset of skin lesion photos. The approach offers several advantages, including high accuracy in identifying skin

lesions and cancer, automation facilitating doctors in patient diagnosis, and the potential for improved treatment outcomes through early detection. However, there are notable challenges and considerations. These include a dependency on diverse, accurately labeled datasets for success, the substantial processing power required by deep learning models, and the inherent lack of interpretability in these models, potentially leading to a less transparent decision-making process. [7] The study employs a hybrid methodology, integrating traditional machine learning methods with deep learning approaches. CNNs, a form of deep learning, are employed to extract features from skin scans. Following their extraction, these characteristics are fed into well-known machine learning techniques like Random Forest and Support Vector Machines (SVM) to identify melanoma. The advantages of this approach include enhanced classification accuracy through the synergy of deep learning and traditional machine learning, the extraction of complex features from images facilitated by deep learning, and improved model interpretability compared to relying solely on deep learning. However, potential drawbacks include increased model complexity due to the combination of two methods, a dependence on substantial and properly categorized data for success, and the requirement for significant computational resources, particularly for certain resource-intensive deep learning components.

[8] The research employs a combination of machine learning and image processing techniques to identify melanoma skin cancer. Initially, image features undergo preprocessing to enhance their characteristics, followed by the application of various methods to extract these features. Subsequently, these enriched features serve as the basis for training machine learning models, including Random Forest and Support Vector Machines, facilitating effective categorization. The method offers several advantages, such as non-invasiveness, providing rapid and accessible melanoma detection using readily available picture data. It also supports early detection, potentially improving patient outcomes. However, there are associated challenges, including the impact of data quantity and quality on accuracy, reduced interpretability compared to deep learning techniques, and potential performance limitations, particularly in complex melanoma cases when compared to deep learning-based approaches. [9] In this study, the skin cancer categorization approach is illustrated using HAM 10000 dataset. The suggested Deep CNN, VGG16, and VGG19 networks are implemented, trained, and evaluated, with a detailed description of the network parameters, training procedure, and dataset pre-processing techniques. The Deep CNN exhibits superiority over VGG16 and VGG19 in terms of overall average accuracy and loss. Notably, the network demonstrates resistance to overfitting, as indicated by minimal variation in accuracy and loss between training and testing phases. The Deep CNN's confusion matrix further attests to the accurate categorization of anticipated outcomes. On the downside, the effectiveness of the DCNN models is highly contingent on the caliber and variety of the dataset used. If the HAM 10000 dataset lacks diversity or comprehensive representation of various skin cancer forms, questions may arise regarding the model's applicability to real-worldcases.

[10] The proposed method aims for the recognition and classification of skin cancer through the application of machine learning and image processing techniques, with a focus on early detection for effective treatment and prevention. Prior to using dermoscopic images as input, preprocessing techniques such as hair removal, image smoothing, and color-based k-means clustering for segmentation are applied. The extraction of statistical and textural features involves the utilization of the Gray Level Cooccurrence Matrix (GLCM) and Asymmetry, Border, Color, and Diameter (ABCD) metrics. For classification, the Multi-class Support Vector Machine (MSVM) is employed. Despite achieving a high accuracy of approximately 96.25% in the experimental analysis, there is acknowledgment that there might be room for improvement in specific cases, emphasizing an ongoing commitment to refining and advancing the methodology. [11] The study aimed to automate the discrimination between benign tumor lesions and skin cancer, developing a CNN model comprising three hidden layers and employing various optimizers. Utilizing the International Skin Imaging Collaboration (ISIC) dataset, encompassing squamous cell carcinoma, melanoma, dermatofibroma, and nevus pigmentosus, the proposed CNN model demonstrated superior performance compared to other skin cancer classification systems, achieving a striking 99% accuracy in finding skin lesions within the ISIC dataset. However, the success of the CNN model hinges on the caliber and diversity of the datasets used. The limited diversity in the ISIC dataset, representing various forms of skin cancer, raises concerns about the model's generalizability to real-world scenarios. While the paper mentions the use of a three-hidden-layer CNN model, the lack of details regarding architecture, hyperparameters, and rationale for this choice complicates the assessment of the model's complexity and suitability for the task.The study proposes a deep learning approach employing computer-based methods to effectively differentiate between non- cancerous and malignant skin lesions, aiming to detect various skin diseases. Initial steps involve data preprocessing and augmentation before the application of CNN and six transfer learning models (Resnet-50, VGG-16, Densenet, Mobilenet, Inceptionv3, and Xception) on the HAM10000 dataset for classification. Despite the creation of five stacking models, overall accuracy remains at 78 percent, indicating suboptimal performance. Notably, the CNN model achieves 77 percent accuracy, while transfer learning models exhibit a range of 82 to 90 percent accuracy. Evaluation measures such as accuracy, F1 score, precision, and recall provide insights into the models' effectiveness in diagnosing malignant cells. The proposed deep learning method holds promise in accurately identifying and categorizing skin cancer, potentially facilitating early detection, treatment, and a reduction in mortality rates.

Numerous publications address the categorization of nevus and melanoma in digital photographs for the purpose of diagnosing skin cancer. A computer approach that uses the Xception model for classification is proposed in one study, and it obtains a 90.24% accuracy rate. A different study suggests a parallel CNN architecture that extracts features and classifies them using a deep learning structure after applying color map histogram equalization and fuzzy systems for edge detection and image enhancement.
In the third work, an automated deep learning system utilizing a CNN model for intensity value estimate is developed, resulting in high levels of accuracy, sensitivity, specificity, and precision.
In the fourth study, a quick dermoscopy image analysis system with an 83% accuracy rate is designed employing support vector machine classification and gray level co-occurrence matrices. In conclusion, a research presents three distinct approaches for binary classification that leverage CNN architectures and achieve excellent F1-score, accuracy, sensitivity, specificity, and precision. [6] The paper presents a deep learning model for skin disease detection and classification using computer-aided diagnosis tools to automate examinations. The architecture includes a cost-sensitive model with a loss function considering factors like predicted output, target value, cost with class, and predicted class. The model demonstrates a 4% improvement in skin disease detection and a 9% enhancement in classification accuracy compared to existing deep learning models. Positioned as a valuable resource for early skin diagnosis in healthcare, the tool supports dermatologists. Concerns include data limitations, requiring diverse skin cancer datasets for model generalizability, and addressing imbalanced data to prevent biased performance in medical datasets.
The study introduces a decision support system utilizing a Convolutional Neural Network (CNN) for skin cancer detection and classification. Employing the MNIST HAM-10000 dataset of dermoscopy images, the system applies image processing and deep learning for diagnostic purposes. Techniques such as noise removal, image resolution enhancement, and image augmentation are employed to enhance the dataset. Transfer learning, specifically employing the ResNet model, is utilized to improve classification accuracy. The CNN model achieves notable metrics, including an average precision of 0.88, a recall average of 0.74, and a weighted f1-score of 0.77. The ResNet-based transfer learning approach attains an accuracy of 90.51%. However, the paper underscores concerns, such as potential overfitting in CNN models, emphasizing the necessity for appropriate regularization and cross-validation. [16] A comprehensive and methodical assessment of deep learning methods for early skin cancer diagnosis is presented in this work. Researchers analyze papers from reputable journals, presenting findings through tools, graphs, and tables. Deep learning shows promise, utilizing lesion parameters for effective benign-malignant distinction. It has the potential to boost diagnostic accuracy and efficiency. Drawbacks include extensive training needs for neural network-based methods, requiring time and powerful hardware. Challenges arise in diagnosing earlier stage and smaller lesions, increasing error susceptibility. The study underscores deep learning's significance while acknowledging practical challenges, emphasizing its critical role in advancing skin cancer diagnosis despite associated complexities.

III. RESEARCH STRATEGY

Our alternative to the existing system is to use a fully automatedneural network model SCDC-Net to detect and classify the skin .Academic results and other aspects are taken into consideration inaddition to emotive study of pupils' mindsets.

- We considered image datasets from ACS and Cancer Research UK as it includes a collection of all important diagnostic categories.
- These datasets have two-third of its images belonging to the Melanocytic nevi class, image augmentation will be implemented to balance the dataset.
- Hair removal technique like UG-Net model will be implemented.
- Hybrid U-Net model will be used for Automatic Skin Lesion Segmentation.
- Recent research indicates that deep learning-based automated skin lesion identification has attained great performance. In particular, methods based on Deep Convolutional Neural Networks may effectively extract and learn the needed deep characteristics from the input photos.
- Deep Q Neural Network model will be implemented to detect skin cancer and classify it into different types.

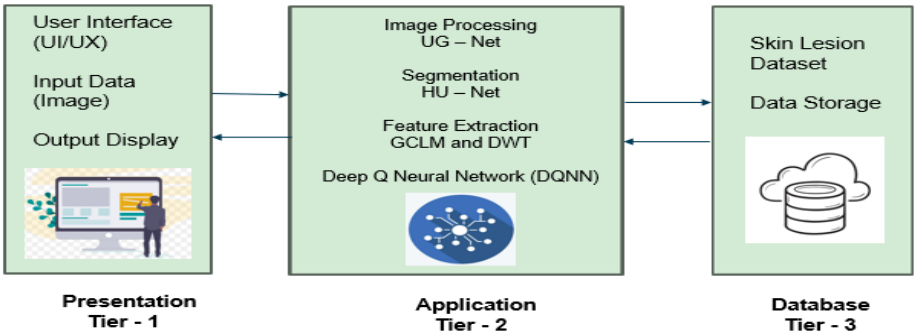


Figure1. Architecture

A. Data Collection and Preprocessing Module

The technique ensures a comprehensive dataset by gathering various photos of skin lesions from medical databases. Data is merged, such as lesion nature and patient demographics. In order to improve diversity, data augmentation techniques are used and ethical issues are given priority. Updates on a regular basis keep the dataset flexible and relevant for reliable skin cancer identification.

B. Hair Elimination and Segmentation Module

The Hair Elimination and Segmentation module is integral in refining skin lesion images for accurate detection. Employing the UG-Net model, a fusion of U-Net and GAN, it effectively eliminates hair interference, enhancing the region of interest. Subsequently, the Hybrid U-Net (HU-Net) ensures precise segmentation, isolating relevant features within the lesion. This sophisticated module guarantees a clean input for further analysis, overcoming challenges posed by hair artifacts and facilitating optimal segmentation for robust skin cancer detection and classification.

C.Feature Extraction Module

In order to implement a feature extraction module for skin cancer detection and classification, Gray Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transform (DWT) must be integrated. Texture patterns are captured by GLCM, and frequency information is extracted via DWT. Combining these methods improves the model's capacity to identify minute details for precise skin cancer diagnosis.

D.Training and Testing Module

Divide the images into testing and training sets. The training set is used for training purpose for your machine learning

model, while the testing set isused for evaluation of its performance. The purpose of this split is to simulate real-world scenarios where you need to make predictionson new, unseen data. By training on one portion of your data and testing on another, you can assess how well your model generalizes to new data. Selecting the right model is a critical decision. It depends on the nature of your data and the specific problem you're trying to solve.Different deep learning algorithms have strengths and weaknesses for various types of tasks, such as classification or clustering. Consider factors like the size of your dataset, the type of data (e.g.,structured or unstructured), and the complexity of the problem. Common models include, neural networks, HU-Net, UG-Net, GLCM, DWT, DQNN. The training phase involves feeding your chosen model with the data from the training set. The model learns from this data to make predictions or classify data points correctly.

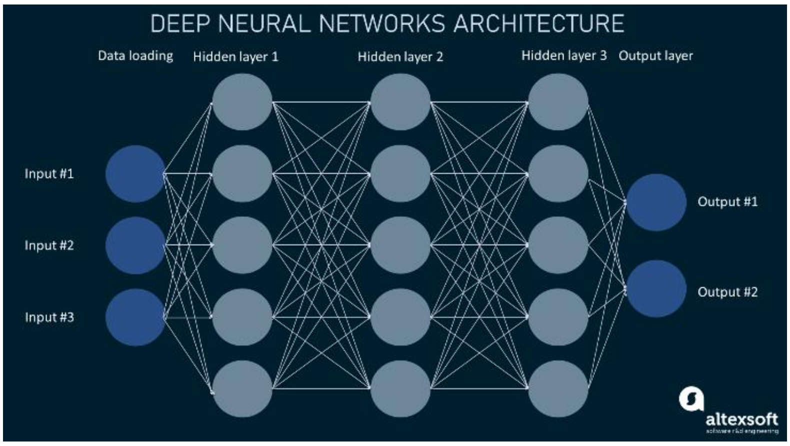
The goal during training is to optimize the model's internal parameters (weights and biases) so that it can make predictions as accurately as possible on the given task. This is done by adjusting these parameters based on the error between the model's predictions and the actual outcomes in the training data. After your model is trained, it's essential to evaluate its performance using the testing set. This is an important phase since it evaluates the model's performance on new, untested data, which is the ultimate objective.

The testing phase involves using the trained model to makepredictions on the testing set. You then compare these predictionsto the actual values in the testing set to assess the model's accuracy, precision, recall, F1-score, or other relevant evaluationmetrics.

In order to evaluate the accuracy and dependability of the trained DQNN model in identifying various types of skin lesions, testing involves feeding input skin photos into the model. The model's predictions are then compared with the ground truth labels. The model's performance is validated by this iterative testing procedure, which also helps to adjust parameters as needed.

Deep Q Neural Network(DQNN)

Through the process of learning complex patterns from a variety of skin photos, DQNN, or Deep Q-Network with Neural Network, can improve the detection of skin cancer. DQNN maximizes feature extraction by adjusting its response to changes in lesion appearances through reinforcement learning. Classification accuracy is improved by this model's capacity to make defensible conclusions based on cumulative information. DQNN's ability to adapt dynamically to new data makes it an important tool in changing circumstances, helping to improve the robustness and reliability of skin cancer diagnoses—a critical component of prompt and effective medical interventions.



E. Detection and Classification Module

In the detection module, user inputs collected through a user interface using Python which are promptly cleaned to address missing or inappropriate images. This cleaned data is then fed into a prediction engine, powered by deep learning techniques like DQNN, which generates real-time predictions and insights based on the user-provided information. These predictions are subsequently displayed on the website, enabling users to immediately access and benefit from the model's assessments.

F. Integration Module

In the integration module, the model incorporates a demonstrative application, employing Python with Redux for thefrontend and Flask for the backend, to simulate the submission ofcomments or posts. Upon submission in user interface, transferring the submitted data as input to the deeplearning model previously described. The model processes the data and promptly conveys its prediction—whether there is cancer or not and if there is cancer it classifies the type of cancer—to the frontend, where the result is dynamically displayed on the screen, ensuring seamless interaction between the user interface and the predictive model.

IV. RESULTS

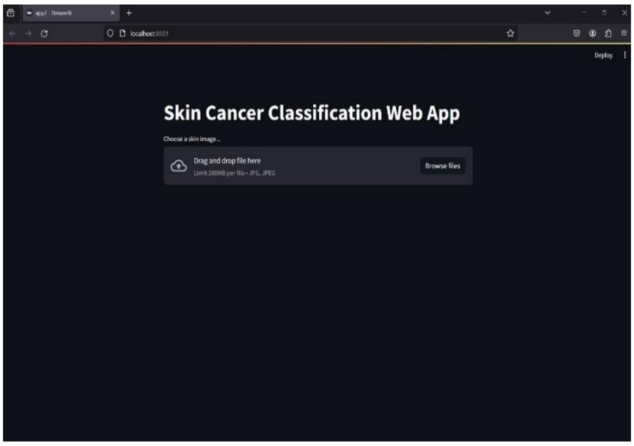
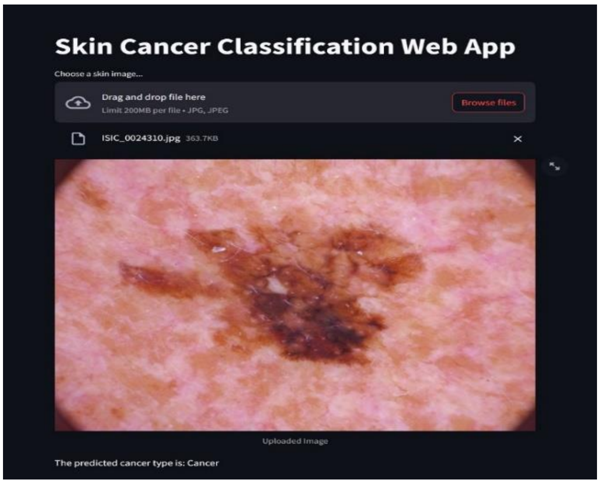


Fig 1: User Interface



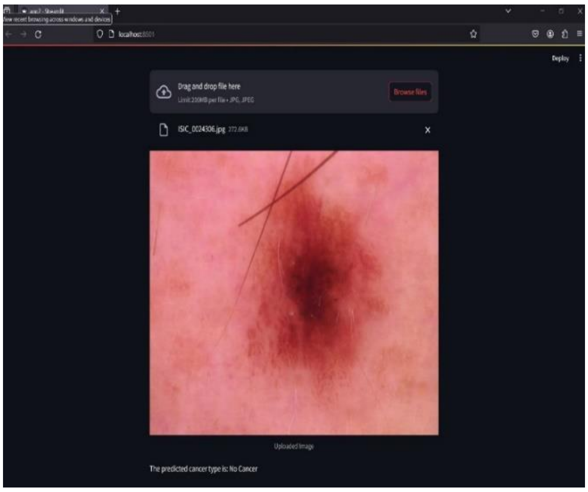
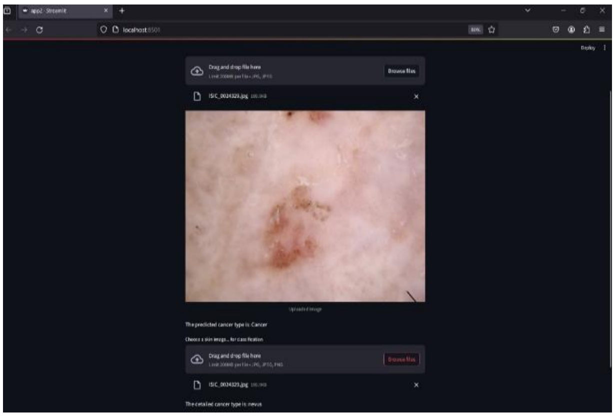


Fig 2: Non-cancerous input (Detection) **Fig 3: Cancerous input**



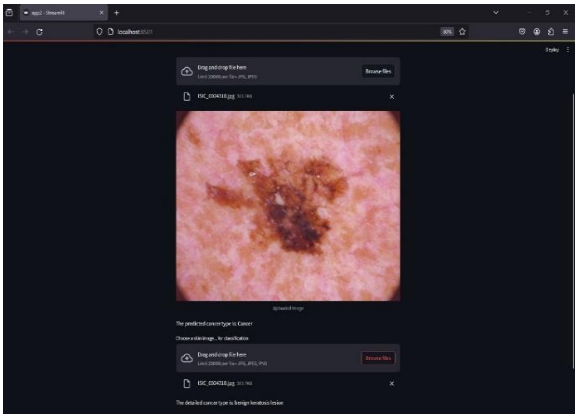


Fig 4 : Classified Output1 **Fig 5: Classified Output2**

V. CONCLUSION

Traditional skin cancer detection methods struggled due to poor feature analysis. This paper tackled this by using transfer learning and advanced networks like UG-Net (combining U-Net and GAN for hair removal) and HU-Net (for refined segmentation) to extract robust features. The model also employed DWT and GLCM for multi-level feature extraction, feeding a DQNN model for accurate classification. The SCDC-Net achieved significantly better results than traditional methods, paving the way for early diagnosis and potentially saving lives. Further research with larger datasets, real-world testing, and integration with existing medical systems can refine this promising approach and revolutionize skin cancer diagnosis.

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