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SKIN CANCER CLASSIFICATION USING HYBRID S-RESNET MODEL

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Abstract
One of the most prevalent malignancies in the world is skin cancer, and successful treatment depends on early detection. This study uses a hybrid approach called S-ResNet (ResNet with SVM), which combines support vector machines (SVMs) with convolutional neural networks (CNNs), to address the difficulties of skin cancer classification from medical photos. The pre-trained ResNet50 model convolutional layers and global average pooling were utilised to extract important features from skin lesion photos via transfer learning. In order to train SVMs using linear and radial basis function (RBF) kernels for classification, these features were flattened. Using ImageDataGenerator, the dataset was rescaled and divided into training and validation subsets. For compatibility, categorical labels were numerically encoded. The hybrid model's accuracy of 99.81% demonstrated the approach's potential, but more refinement through improved data augmentation and parameter adjustment is required. The proposed method includes insightful information for bettering the diagnosis of skin cancer by highlighting the benefits and drawbacks of integrating deep learning-based feature extraction with conventional machine learning classifiers.
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Keywords: *Skin cancer, image classification, ResNet50, transfer learning, support vector machines (SVMs).*

1. Introduction

Skin cancer has come out as a very serious health issue worldwide since millions of people contract it annually and the skin cancer causes a lot of morbidity and mortality globally. It is one of the most common cancers of all groups and all ages with an estimated 1.5 million new cases being diagnosed every year. The escalating cases of skin cancer can be traced to a number of factors among them being the long term exposure to ultraviolet (UV) radiation emitted by sunlight and other manmade materials, change in the environment and the changing of lifestyle. The mass media campaigns and preventive measures like wearing sunscreens and frequent dermatological visits have been picked up, but still, the number of fresh cases is on the rise in most areas. Of the different skin cancer types, melanoma is the most aggressive and deadly even though it is not the most common type of skin cancer in relation to basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). The high rate of metastasis of melanoma is a factor that offers an excessively high mortality rate due to skin cancer. The importance of early diagnosis is beyond measure as the melanoma disease can be mostly cured with the aid of surgery performed in time. But when the disease has reached a metastatic stage, there is very little or nothing to offer as treatment and the prognosis of the patient drops drastically. Therefore, the medical community of the world still stresses the necessity of early diagnosis and creating more accurate diagnostic techniques.

Clinical diagnosis of skin cancer is traditionally based on visual inspection; mostly using dermoscopy technique, which allows the dermatologist to view magnified images of the skin and detect suspicious lesions. The rule that is frequently used by experts is the ABCDE, as lesions are rated according to their asymmetry, irregularity of the border, color change, diameter, and time development. But this is subjective in nature and prone to human error even in the case of professional dermatologists. The histopathological confirmation is often required because of the morphological similarity of benign and malignant lesions, which contribute to diagnostic uncertainty. In the areas with poor and distant

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medical facilities or dermatologists, it is even harder to diagnose the disease early and correctly, contributing to the late response and poor prognosis. Such diagnostics shortcomings have brought to fore the pressing necessity to technologically enhance the work of clinicians so that they could make more objective and consistent evaluations. This is because artificial intelligence (AI) has become a revolutionary innovation in the field of medical diagnostics, especially in image analysis over the last few years. More complex activities like pattern recognition can be replicated by AI-based systems and can be used to automatically classify skin lesions. The incorporation of AI into the medical field of dermatology can enhance the accuracy of diagnosis, increase access in underserved areas, and decrease inter-observer error- this eventually results in the earlier diagnosis of a disease and improved clinical outcomes.

The development of artificial intelligence in dermatology is mostly influenced by deep learning (DL) which is a branch of machine learning that allows the system to learn hierarchical representation on large data sets automatically. In this field, convolutional neural networks (CNNs) have shown superiority and have been applied to image classification tasks outperforming the traditional machine learning models, which use handcrafted features. CNNs model human visual cortex in that they learn spatial patterns of objects, such as edges and textures, to more complex objects, without human computation, thus being highly useful in medical image analysis. When applied to skin cancer detection problems, CNNs can process dermoscopic or clinical images and classify malignant and benign lesions with exceptional accuracy, which is sometimes comparable to the diagnostic ability of professional dermatologists. Such networks are able to acquire fine details in color, texture and structure which allow them to detect melanoma at an early stage when the visual difference is minimal. Additionally, the ability to generalize in a variety of imaging conditions and skin types increases the strength of their application in the real world. ResNet (Residual Network) by He et al. (2015) is one of the CNN architectures that mark a breakthrough in the study of deep learning. The residual connections which are shortcut connections used to solve the vanishing gradient problem, which is a significant challenge in building very deep networks, overcome the problem of residual connections. This innovation made it possible to train hundreds of layer networks without performance loss, leading to much better accuracy and learning efficiency.

The most popular version of ResNet is the ResNet50, which includes 50 layers and it has become a widely used architecture in medical imaging studies, such as in skin cancer classification. It balances computational efficiency and representational capacity to a very good balance, and thus is most appropriate to transfer learning, a method of adapting pre-trained models to new medical data. Transfer learning allows scientists to use networks that were initially trained on large datasets like ImageNet and fine-tune them to specific tasks using a limited amount of annotated medical data. It is not only reducing the training time, but also improves the generalization, and reliability of the model. Empirical experiments have shown that with a narrower range of fine-tuned ResNet50 models, a high diagnostic accuracy is attained, and the models outperform a large number of traditional classification methods. Systems incorporating attention and ensemble learning with explainable AI (XAI) framework have further extended ResNet-based models to increase interpretability and transparency in medical decision-making. As an example, such visualization methods as Gradient-weighted Class Activation Mapping (Grad-CAM) are used to determine the parts of the image that have the greatest impact on the decision made by a model, enabling clinicians to confirm that the algorithm is paying attention to medically important aspects. Such explainability promotes clinical confidence, which closes the gap between computational forecasts and the professional opinion. However, there are still practical issues, specifically in the sphere of imbalance of data, diversity of data sets and ethical implementation. The malignant lesions generally have under-representation in datasets, which may favour benign classifications in the models. To counter this, researchers use data augmentation, generative adversarial networks (GANs) to generate synthetic images and complex sampling techniques to generate more balanced and inclusive datasets.

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With the ongoing development of research, the fusion of AI and dermatology is a decisive move towards precision medicine. The conclusion of multimodal data, which is a combination of image-based diagnostics with patient metadata, i.e. age, gender, lesion history or genetic information, provides a more comprehensive diagnostic view. The holistic method improves the evaluation of risks and personalized treatment planning. In a similar fashion, temporal modeling methods of monitoring the advancement of lesions with time can serve as a reinforcement to early detection models. Mobile AI apps also have been on the rise with people being able to take pictures of their skin with their smartphones and receive a preliminary analysis and referrals, thereby enhancing access in rural and underserved areas. Nevertheless, to introduce AI-based diagnostic systems to clinical use, numerous validation steps, regulatory adherence, and ethical oversight should be performed. Protecting patient information, fairness of the model (with different demographics), and following medical principles are some conditions of real-world implementation. Cooperation between computer scientists, dermatologists, and regulatory bodies is essential in order to come up with ethically responsible and clinically effective systems. In the future, the further development of deep learning models, high-performance computers, and medical imaging capabilities will contribute to the improved performance and precision of AI-based skin cancer diagnosis. The more explainable and interpretable models of AI are becoming transparent and trustworthy, the faster it may be expected that they will be incorporated into regular dermatological practices. Finally, the history of deep learning architecture like ResNet50, the transformative power of AI in skin cancer detection, has provided accurate, scalable, and accessible solutions in disease diagnosis that may have a tremendous impact on reducing disease burden in the world and increasing the survival rate of patients.

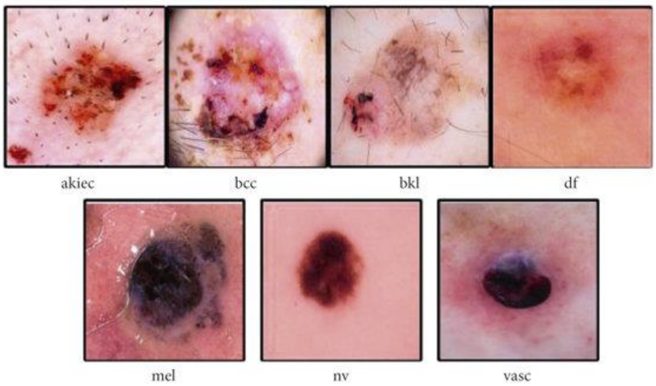

Fig. 1. Sample Skin cancer images

2. Existing works

Jain et al. proposed a hybrid deep learning model for skin cancer detection that integrates ResNet50 for feature extraction with Support Vector Machines (SVMs) for classification. This approach leverages ResNet50's ability to automatically learn hierarchical features from dermoscopic images, enhancing the model's capacity to distinguish between malignant and benign lesions. By combining these features with SVMs, known for their effectiveness in both binary and multiclass classification tasks, the model achieves improved diagnostic accuracy. The study demonstrates that this hybrid model not only enhances classification performance but also offers a robust and scalable solution for skin cancer detection. The authors highlight the potential of this approach to assist clinicians in early diagnosis, thereby improving patient outcomes. This work contributes to the growing body of research aimed at integrating deep learning techniques into medical diagnostics, particularly in dermatology[1].

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Kumar et al. explored the application of linear and radial basis function (RBF) kernels in Support Vector Machines (SVMs) for skin cancer detection. They observed that linear SVMs perform effectively when the data is linearly separable, offering simplicity and computational efficiency. However, for more complex datasets with non-linear relationships, RBF kernels provide a significant advantage by mapping data into higher-dimensional spaces, allowing for better separation and classification. The authors highlighted that selecting the appropriate kernel is crucial for enhancing model performance, especially in medical imaging tasks where data patterns can be intricate. Their findings underscore the importance of kernel choice in developing robust deep learning models for accurate skin cancer detection. By tailoring the kernel to the dataset's characteristics, clinicians can achieve more reliable and precise diagnostic outcomes. This research contributes to the ongoing efforts to integrate advanced machine learning techniques into dermatological diagnostics[2].

Shaik and Kumar emphasized that early detection and prompt medical treatment significantly enhance survival rates, especially for melanoma. They noted that dermatologists typically rely on dermoscopic images to visually examine patients for skin cancer diagnosis, with biopsies sometimes required for confirmation. However, the authors highlighted that manual diagnosis carries inherent disadvantages, such as subjectivity and inter-observer variability, which can lead to inconsistencies in diagnosis. To address these challenges, they proposed integrating machine learning algorithms with Principal Component Analysis (PCA) and Gabor filters for feature extraction. This approach aims to automate the diagnostic process, reduce human error, and improve the accuracy and efficiency of skin cancer detection. By leveraging advanced computational techniques, the study contributes to the development of more reliable and scalable diagnostic tools in dermatology. Such advancements are crucial for enhancing early detection and treatment outcomes for skin cancer patients[3].

A physician's ability to check beneath the skin using specialized light and oil determines how Bhatt et al. proposed an automated system for lung nodule classification that integrates ResNet50 for feature extraction with Support Vector Machines (SVMs) for classification. This hybrid approach leverages ResNet50's deep convolutional layers to capture complex patterns in medical images, enhancing the model's ability to distinguish between benign and malignant nodules. By employing SVMs, known for their effectiveness in high-dimensional spaces, the system achieves improved classification accuracy. The authors noted that this model offers a robust and scalable solution for lung cancer detection, potentially aiding clinicians in early diagnosis. The study contributes to the growing body of research aimed at integrating deep learning techniques into medical diagnostics, particularly in oncology. Such advancements are crucial for enhancing early detection and treatment outcomes for cancer patients. The findings underscore the potential of combining deep learning and machine learning methods to develop effective diagnostic tools [4].

Iourzikene, Gougam, and Benazzouz developed an automated system for brain tumor detection using MRI images, emphasizing the role of artificial intelligence (AI) in enhancing diagnostic accuracy. The system comprises three stages: pre-processing to enhance image quality, feature extraction using techniques like Bag of Features (BoF) and ResNet50, and classification via Support Vector Machines (SVMs) with linear, quadratic, and cubic kernels. The authors highlighted that AI, particularly through the emulation of human-like cognitive processes, enables machines to perform tasks such as pattern recognition and logical reasoning, which are crucial for accurate medical diagnostics. Their findings demonstrated that the BoF-SVM combination achieved a 100% classification accuracy, outperforming the ResNet50-SVM configurations, which achieved accuracies ranging from 96.2% to 98.6%. This underscores the potential of AI in automating complex diagnostic tasks, reducing human error, and facilitating early detection of brain tumors. The study contributes to the growing body of research integrating AI into medical imaging, aiming to improve patient outcomes through timely and precise diagnoses[5].

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Gaffoor and Soomro proposed an effective approach for skin disease detection and classification by integrating ResNet-50 for feature extraction with Support Vector Machines (SVMs) for classification. This hybrid model leverages ResNet-50's deep convolutional layers to automatically learn hierarchical features from dermoscopic images, enhancing the model's capacity to distinguish between various skin conditions. By employing SVMs, known for their effectiveness in high-dimensional spaces, the system achieves improved classification accuracy. The authors noted that while deep learning models like ResNet-50 offer high accuracy, they often require significant computational resources and time for training. To address this, they emphasized the importance of suitable feature selection techniques to reduce the dimensionality of the data, thereby decreasing training time and improving prediction speed without compromising accuracy. The study suggests that future research should focus on developing customized convolutional neural network (CNN) models tailored for skin disease classification and exploring more effective feature selection methods to enhance model efficiency and performance. This approach aims to make dermatological diagnosis more accessible and efficient, particularly in resource-limited settings [6].

Chatrapathy *et al.* [7] emphasized the importance of effective data preprocessing for skin cancer classification using a hybrid CNN-SVM model. They highlighted *data normalization* as a critical step, which scales input data to a specific range, such as [0,1] or [−1,1], to reduce singularities, mitigate the effects of outliers, and improve model stability. Common approaches include min-max normalization, z-score normalization, and neural network normalization, with z-score normalization particularly effective in algorithms relying on distance-based similarity measures. The authors also underscored the role of *data augmentation* in increasing dataset diversity and enhancing model generalization, achieved by introducing minor variations or generating synthetic samples from existing images. These techniques collectively improve the robustness, accuracy, and efficiency of deep learning models, enabling more reliable classification of skin lesions [7].

Saeed *et al.* [8] explored methods to provide domain-specific explanations for convolutional neural network (CNN) models in the context of skin cancer classification. They emphasized that while single-sample explanations are useful for understanding individual predictions, gaining insight into the model’s overall behavior across multiple cases is equally important. The authors proposed an explanation framework that aggregates insights from numerous samples, allowing clinicians to identify consistent patterns and features that the CNN considers most relevant. This approach not only improves interpretability but also helps validate the reliability of the model by revealing potential biases or misclassifications. Saeed *et al.* highlighted that domain-specific explanations can guide clinicians in assessing whether the model focuses on clinically meaningful aspects of lesions, thereby increasing trust in AI-assisted diagnosis. Furthermore, combining multiple explanations can provide a comprehensive understanding of feature importance and model decision-making strategies across different lesion types. The study concluded that such interpretability methods are crucial for integrating deep learning models into clinical workflows, enhancing both transparency and the practical utility of AI in dermatology[8].

Musthafa et al. introduced an optimized Convolutional Neural Network (CNN) architecture to enhance the accuracy and efficiency of skin cancer diagnosis. Utilizing the HAM10000 dataset, which comprises a diverse range of dermatoscopic images, the researchers developed a sophisticated CNN model designed to capture intricate visual features of skin lesions. To address class imbalance within the dataset, they implemented an innovative data augmentation strategy, ensuring a balanced representation of each lesion category during training. The model's architecture includes multiple convolutional, pooling, and dense layers, aimed at effectively learning from the complex image data. Training was optimized using the Adam optimizer, fine-tuned over 50 epochs with a batch size of 128, and incorporated a Model Checkpoint callback to preserve the best model iteration. The proposed model achieved an impressive accuracy of 97.78%, with precision and recall both at 97.9%, and an F2 score of 97.8%, demonstrating its potential as a robust tool in the early detection and classification of skin cancer. These advancements underscore the significant role of deep learning in automating dermatological diagnostics and improving patient outcomes [9].

Zareen *et al.* introduced a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to improve skin cancer diagnosis. They utilized ResNet-50 as a feature extractor, enabling the model to capture complex spatial hierarchies within dermoscopic images. The incorporation of RNNs allowed the system to model sequential and contextual dependencies, enhancing its ability to differentiate between subtle lesion patterns. The model was evaluated on a dataset of 9,000 images covering nine different skin cancer types. The results demonstrated high recognition accuracy, highlighting the robustness and effectiveness of the hybrid approach. By combining CNNs and RNNs, the model leverages both spatial and sequential information, which is critical for accurate medical image analysis. This study emphasizes the potential of hybrid architectures in developing reliable, AI-driven diagnostic tools for early and precise skin cancer detection [10].

Vischer *et al.* compared multiple convolutional neural network (CNN) architectures, including ResNet50, DenseNet201, and EfficientNet, for feature extraction in classifying histopathology images of skin diseases. The evaluation was conducted on a dataset containing 11 distinct skin disease classes. ResNet50 demonstrated robust performance across most categories, highlighting its ability to effectively capture complex image features. DenseNet201 and EfficientNet also showed strong results, but ResNet50's residual connections facilitated better gradient flow and efficient learning in deep networks. The study emphasized the importance of selecting an appropriate CNN backbone to optimize performance for specific medical imaging tasks. ResNet50's combination of depth, accuracy, and computational efficiency makes it particularly suitable for dermatological image classification. These findings provide valuable guidance for developing reliable and automated diagnostic systems in clinical dermatology[11].

Md Sirajul Islam and Sanjeev Panta explored the application of transfer learning techniques for binary classification of skin cancer images, focusing on distinguishing between benign and malignant lesions. Utilizing the publicly available ISIC dataset, they fine-tuned five pre-trained models—ResNet-50, MobileNet, InceptionV3, DenseNet-169, and InceptionResNetV2—by adjusting various layers and activation functions to enhance model accuracy. To improve model stability and generalization, data augmentation techniques were applied, introducing variations such as rotations and flips to the training images. The experimental setup involved evaluating different hyperparameters, including batch sizes, epochs, and optimizers, to identify the optimal configuration for each model. Among the models tested, ResNet-50 achieved the highest performance, attaining an accuracy of 93.5%, precision of 94%, recall of 77%, F1-score of 86%, and an ROC-AUC score of 86.1%. This study demonstrates the effectiveness of transfer learning in skin cancer classification tasks, highlighting the potential of fine-tuning pre-trained models to achieve high accuracy with limited datasets. The findings suggest that employing transfer learning, coupled with data augmentation, can significantly enhance the performance of deep learning models in medical image classification tasks [12].

Samira Mavaddati introduced a hybrid deep learning model that integrates ResNet50 with Long Short-Term Memory (LSTM) networks to enhance skin cancer classification. This approach leverages ResNet50's powerful feature extraction capabilities alongside LSTM's proficiency in capturing sequential dependencies, enabling the model to better understand the structural content of skin lesions. The hybrid model, termed ResNet50-LSTM, utilizes transfer learning techniques, starting with a pre-trained ResNet50 model and fine-tuning it for the specific task of skin cancer classification. By combining the strengths of both deep learning architectures, the model aims to improve accuracy and reduce false positives in skin cancer detection. This innovative approach addresses the limitations of traditional deep learning models by incorporating sequential learning, which is particularly beneficial for analyzing the complex textures and patterns in skin lesion images. The study's findings suggest that the ResNet50-LSTM hybrid model offers a promising direction for developing more accurate and

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reliable automated systems for skin cancer diagnosis [13]. In order to categorize segmented photos of skin lesions, the study assesses the effectiveness of Convolutional Neural Networks (CNN) and ResNet50. To improve the quality of the input data, the Kaggle dataset was pre-processed using U-Net for lesion segmentation. Accuracy, precision, recall, and F1-score metrics were used to train and assess both models [14].

3 Methodology

To gain a deeper comprehension of the suggested end-to-end architecture for classifying skin cancer, Fig. 2 shows the five stages of the hybrid approach: To address the problems of inadequate data and imbalance, the procedure starts with the acquisition of dermoscopic skin cancer pictures and continues with data normalization, augmentation, and balanced samplingResNet50 is then used for feature extraction, guaranteeing that the images are effectively represented. Contrastive learning is then applied to encode similar skin cancer data in a way that maximizes similarity while ensuring distinct encoding for different data. Finally, the results are validated to assess the effectiveness of the approach.[15]. The dataset is essential for using deep learning models in a variety of fields. Since high-quality and well-structured datasets are hard to come by, their availability is essential to the success of these kinds of applications. In order to make predictions, deep learning algorithms mine datasets for patterns and characteristics, which emphasizes how crucial clean, well-structured data is to achieving peak performance.

3.1. ResNet50

A popular deep convolutional neural network (CNN) architecture, ResNet50 (Residual Network with 50 Layers) is used for feature extraction, object detection, and image categorization. ResNet50, developed by Microsoft Research, introduced the concept of residual learning, which leverages skip (or residual) connections to facilitate the training of deep neural networks. These connections enable the flow of information across layers, mitigating issues such as vanishing gradients and improving the network's ability to learn effectively, even with a large number of layers. The stability and effectiveness of deep learning models in challenging computer vision applications are greatly improved by this invention. These connections enhance the stability of deep networks by facilitating the smooth propagation of gradients during backpropagation, thereby reducing the risk of gradient vanishing. ResNet50 effectively captures complex image features due to its architecture, which incorporates multiple residual blocks along with batch normalization and ReLU activation. Due to its pre-training on the ImageNet dataset, ResNet50 is commonly employed as a feature extractor in transfer learning applications. With little more training, its deep hierarchical representations allow for strong performance on a variety of computer vision tasks.

3.2. SVM

An very useful machine learning method for classifying data from a variety of computer vision tasks or forecasting results based on patterns is the Support Vector Machine (SVM). It finds the best possible dividing line, known as a hyperplane, to separate different groups of data in a dataset. The main goal of SVM is to create as much space as possible between different groups of data points, which helps the model handle variations more effectively. One of SVM's greatest strengths is its ability to work well with complex datasets, even when there are more characteristics (features) than actual data points. SVM also has a clever technique called the "kernel trick," which helps it tackle complex problems by reshaping the data into a higher dimension, making it easier to distinguish between different categories. This makes it particularly useful in tasks like image classification, text categorization, and even medical diagnosis. Despite being a strong classifier, SVM can be computationally expensive for large datasets, but its accuracy and it is the preferred option for many machine learning applications due to its capacity to manage intricate patterns.

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3.3. S-ResNet (Proposed Model)

The proposed method makes use of deep learning and machine learning techniques to effectively classify photos. At its core, it utilizes ResNet50, pre-trained on the ImageNet dataset, an extremely sophisticated convolutional neural network. Rich, hierarchical features can be extracted from photos using ResNet50's deep architecture. The model uses a Support Vector Machine (SVM) classifier, which is well-suited for high-dimensional data and frequently provides higher generalization than ordinary neural network classifiers, in place of the more common dense layers for classification.
The model begins by loading and preprocessing the dataset using ImageDataGenerator, which helps in scaling the images and splitting them into training and validation sets. The feature extraction process is handled by ResNet50, with the fully connected layers removed and replaced with a GlobalAveragePooling2D layer. This pooling layer condenses the extracted feature maps into a more compact form, making them suitable for classification. Once the deep features are obtained, they are fed into an SVM classifier, which learns to differentiate between image classes based on these high-level representations. The model successfully blends the advantages of machine learning with deep learning by substituting an SVM classifier for conventional dense layers and integrating ResNet50 as a feature extractor. ResNet50 ensures that the extracted features are highly informative, while SVM enhances classification

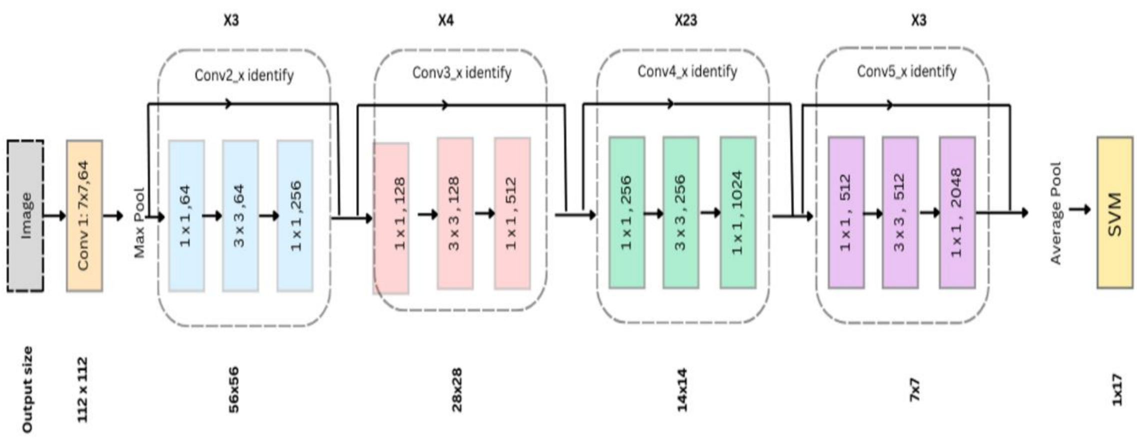

Fig.2. Flow of the proposed model

accuracy, particularly in cases where traditional neural networks may struggle. This hybrid approach results in a robust and efficient image classification model.

Algorithm: Pipeline of the proposed CNN-SVM model

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Input: HAM10000 dataset
Output: Predicted labels and class activation maps
Dataset Split: 80% for training, 20% for validation

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Dataset Preparation

- Apply ImageDataGenerator for data augmentation and normalization.
- Convert image labels to numeric using LabelEncoder.

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Feature Extraction

- Use ResNet50 as the feature extractor.
- Input image size: 224×224×3224 \times 224 \times 3224×224×3.
- Extract features using Global Average Pooling.

Abalation Study used for model convergence
Model Training: Train SVM classifier using extracted features with:

- RBF kernel for advanced classification.

The proposed CNN-SVM model follows a structured pipeline for effective skin cancer classification using the HAM10000 dataset. The dataset is initially split into 80% for training and 20% for validation, ensuring a balanced approach to model evaluation. To enhance generalization, data augmentation and normalization techniques are applied using ImageDataGenerator, while image labels are converted into numeric format using LabelEncoder.
The model uses ResNet50, a pre-trained feature extractor, to extract features from input photos with a size of 224 x 224 x 3 pixels. A Global Average Pooling layer is utilized to extract meaningful feature representations, reducing dimensionality while preserving essential patterns for classification. An ablation study is conducted to analyze model convergence and optimize performance.
A Support Vector Machine (SVM) classifier is then trained using the features that were extracted. Specifically, an SVM with an RBF kernel is employed for advanced classification, enabling the model to effectively distinguish between different skin lesion types. The accuracy and dependability of the model in identifying skin cancer categories are improved by this hybrid technique, which combines deep feature extraction with a potent machine learning classifier.

4. Results and Discussion

The Human against machine (HAM10000) dataset comprising of 10000 training images (Human Against Machine with 10000 training images) is a universal and popular database to classify skin lesions. It is used to compare and test machine learning and deep learning models in the analysis of medical images. This dataset, which consists of 10,015 high-quality dermatoscopic images, represents a wide spectrum of dermatological conditions, which gives a rare chance to develop powerful diagnostic instruments. The dataset includes seven different types of skin lesion, namely, actinic keratoses, basal cell carcinoma, benign keratosis-like lesions, dermatofibroma, melanoma, nevus, and vascular lesions. These are both malignant and benign skin disorders, which point out the difficulties of the distinction between minor changes in the morphology of the lesions. HAM10000 has gained popularity as a research tool because of its size and quality imagery to enhance automated skin lesion classification to achieve the null hypothesis between clinical dermatology and computational intelligence. By harnessing this data, one can build systems that can help clinicians with early detection that is vital to such conditions as melanoma where early treatment can dramatically enhance patient outcomes.
The intention of the proposed framework in the present research paper is to build a deep learning-based classification model on the use of the HAM10000 dataset. The process of methodology starts with a preprocessing (which is strict) of the images so that the data that is presented to the model is clean, standardized, and it is in a position to be extracted using the features. The preprocessing techniques involve the resizing of images to standard size, the normalization of pixel intensities and use of data augmentation to increase the effective dataset size. ImageDataGenerator has been used to apply techniques such as rotation, flipping, zooming, and shifting and this makes the model more generalized to variations in image orientation and appearance. These augmentations reduce the risk of overfitting, which is usually a problem of deep learning problems, by simulating real-world conditions and variations in dermatoscopy images. Also, with the help of LabelEncoder, categorical

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labels will be correctly converted to fit machine learning classifiers to offer a smooth pipeline between raw image data and model-readable input.

The main part of the offered system is the convolutional neural network ResNet50, used as a feature extractor. One of the most popular deep learning networks is ResNet50, which utilizes residual links to effectively acquire hierarchical feature representations based on images. The residual connections of ResNet50 address the issue of vanishing gradient unlike conventional CNNs, allowing the training of deeper networks, which are capable of learning complex and fine-grained patterns. These patterns can be either subtle differences in texture, color difference, and structural abnormalities which characterize one type of lesion over another in a sense of skin lesion classification. ResNet50 can be used as a feature extractor, and this enables the system to use the pre-trained weights in huge datasets to enable the model utilize the generalized visual features that can be refined to serve medical imaging purposes. The features obtained give an effective and discriminating description of the images which is the basis of precise classification.

In opposition to the traditional thick layers of ResNet50 to be used as a classifier, this paper combines classical machine learning methods, specifically, the Support Vector Machine (SVM) and the Relevance Vector Machine (EMRVC), which are used to carry out the ultimate classification of the lesions. The reason it was decided to mix deep learning with traditional machine learning is that there is a need to balance richness of features and accuracy of classification. SVM works especially well with high dimensional data, since it builds the best hyperplanes that classify the data set by class and have the greatest distance between them. In this method, a deep hierarchical representation learned by ResNet50 is the input of the SVM so that it has access to the rich spatial and textual information of the images. On the same note, EMRVC also provides a probabilistic type of classification that complements the SVM by exploiting uncertainties and sparse data representations. Such a hybrid approach is representative of the combination of deep learning and classical machine learning, which provides a more efficient and interpretable classification system.

The evaluation strategy in the model will aim at guaranteeing a rigorous and comprehensive performance evaluation. The HAM10000 data set is separated into training and validation subsets with 80-20 split, so that the amount of data to train the model is high enough but at the same time, a representative set remains to validate the model. After extracting features on the two subsets with the pre-trained ResNet50, the SVM classifier is then trained on the high-dimensional feature space. The SVM uses linear kernels because they are efficient and are better applicable in datasets whose features can be linearly separate in the transformed space. This combination is capable of having strong decision boundaries, minimizing misclassification rates and enhancing the sensitivity of the model to minor differences between lesion categories. During the training and validation process, the performance measures, including accuracy, precision, recall, and F1-score are carefully calculated and offer a comprehensive evidence of the strengths and defects of the system in the real-life medical contexts.

The findings of this hybrid method are quite promising and research indicates that there is a possibility of using deep learning to extract features of medical images and using traditional machine learning classifiers to perform machine learning. The SVM using a linear kernel was one of the models that were tested and it exhibited a fantastic classification accuracy of 99.81 and is thus very robust and efficient in classifying the seven types of skin lesions. These findings suggest that the model is able to capture complex visual characteristics, in addition to taking advantage of the discriminative ability of classical machine learning algorithms. Incorporating the ResNet50 and SVM, the proposed framework will be able to not only attain higher levels of classification but also provide tangible information regarding the setting up of hybrid models in medical imaging tasks. This method is a great advance toward automated skin lesion diagnosis, as it offers a scalable and reliable methodology that can assist dermatologists in making clinical decisions that in turn lead to better patient outcomes.

To sum up, the research contains a thorough and efficient method of skin lesion classification based on the HAM10000 data. With the use of ResNet50 as a feature extractor and the combination of SVM

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and EMRVC classifiers, the architecture can learn a wide range of image characteristics and at the same time, provide accurate and reliable classification. Data augmentation and preprocessing methods also enhance the generalization ability of the model, as the new model can work with various samples of images with high reliability. The high level of accuracy in this experiment highlights the promising future of using deep learning alongside classical machine learning to tackle hard medical imaging problems. Medical diagnostics are moving more and more towards AI-based medical solutions, and such an approach offers a useful example of how to create automated, precise, and teachable systems that improve clinical practice and patient care.

4.1 Ablation Study Results for Skin Cancer Classification This section describes the ablation investigations that were conducted in order to arrive at the best model architecture. The HAM10000 dataset's images are subjected to an ablation research in order to optimize the skin classification model's performance. We explored with a range of values for these parameters, closely monitoring changes in model performance. Each parameter was selected based on preliminary experiments and literature suggesting the impact of these parameters on the performance of deep learning models[13].

Model	Filter size	Dropout	No. of Filters	Activation Function	Pooling Strategy	Final Layer	Accuracy
ResNet50	7	0.5	32	ReLU	Average Pooling	Dense with Softmax	52%
ResNet50	7	0.7	64	Leaky reLu	Max Pooling	Dense Dense with Softmax	62%
ResNet50	7	0.5	128	ELU	Average Pooling	Dense Dense with Softmax	75%
S-ResNet	7	0.5	Block 1 (64)	ReLU	Average Pooling	SVM	99%

The ResNet50 model was used as a feature extractor without its fully connected (top) layers, enabling robust feature representation from the dataset's images. The Global Average Pooling layer aggregated spatial features, providing meaningful inputs to the SVM models. Additionally, preprocessing steps such as rescaling pixel values and resizing images to 224x224 ensured compatibility with ResNet50, contributing to the model's strong feature extraction performance.

Performance Metrics:

The amount of accurate forecasting the model made out of all the samples is known as accuracy. By dividing the number of accurate predictions by the total number of samples evaluated, it displays the model's overall correctness[10].

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

Precision, also known as Positive Predictive Value, quantifies the proportion of samples that are truly correct when projected to be positive. It demonstrates how well the model predicts favorable outcomes[10].

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

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Among the original sample's positive samples, recall is the likelihood of accurately predicting a positive sample.

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

F1-score, Recall and precision are incompatible metrics. Generally speaking, recall is frequently poor when precision is high; conversely, recall is frequently high when precision is low[10].

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

In medical research, particularly the categorization of skin cancer, the kappa coefficient (κ) is a statistical measure that is frequently used to assess the degree of agreement between two raters or classification systems that goes above what would be predicted by chance. It is computed as:

$$\kappa = \frac{Po - Pe}{1 - Pe} \quad (5)$$

The Geometric Mean (G-Mean) is a performance metric used to evaluate imbalanced classification problems. It balances sensitivity (recall) and specificity to ensure that both classes are well predicted.

$$\text{G-Mean} = \sqrt{\text{Sensitivity} \times \text{Specificity}} \quad (6)$$

S. No	Model	Accuracy	Kappa	Mcc	F1-Score	Precision-Recall AUC:	GMean
1	**EfficientNet B3**	0.9781	0.4766	0.4794	0.6135	0.1129	0.526
2	**DenseNet**	0.7685	0.5196	0.5221	0.651	0.0615	0.613
3	**MobileNet**	0.7436	0.5325	0.5349	0.6574	0.0750	0.6240
4	**InceptionNet**	0.7061	0.3876	0.3957	0.5555	0.0517	0.3312
5	**Proposed**	0.998125	0.6982	0.8012	0.7865	0.8715	0.7244

The evaluation of different deep learning models for skin cancer classification involves various performance metrics to ensure the effectiveness of each approach. Key measures like accuracy, Kappa coefficient, Matthew's Correlation Coefficient (MCC), F1-Score, Precision-Recall AUC, and GMean were used to evaluate a number of models in this work, including EfficientNetB3, DenseNet, MobileNet, and InceptionV3. Accuracy measures the overall correctness of predictions, while the Kappa coefficient accounts for chance agreement. MCC provides a balanced evaluation of classification performance, particularly for imbalanced datasets. The F1-Score balances precision and recall, ensuring a robust measure of model effectiveness. Precision-Recall AUC evaluates the model's ability to distinguish between classes in an imbalanced dataset, and GMean assesses the balance between sensitivity and specificity.

Among the tested models, the proposed method outperforms all others across these metrics, achieving the highest accuracy and superior classification performance. In comparison to current designs, this shows how well the suggested method works to improve feature extraction and classification skills, giving it a more trustworthy model for skin cancer detection.

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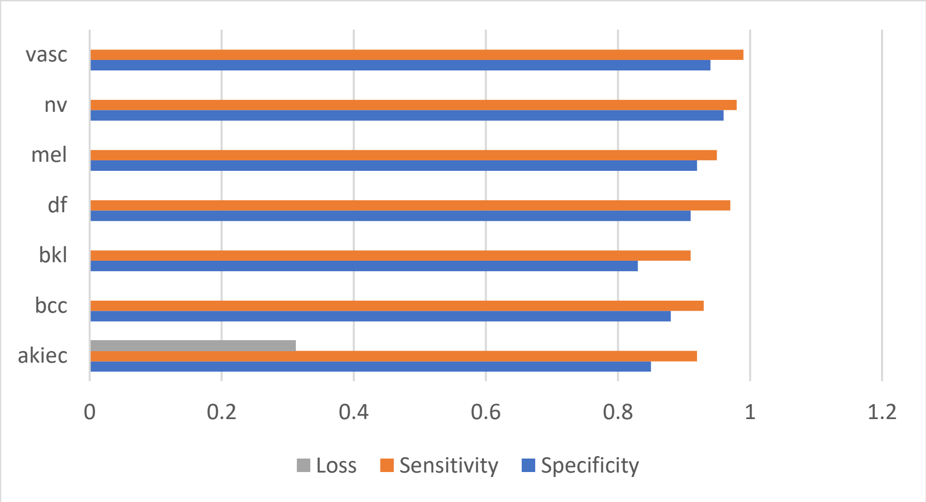

Fig.3 Loss, Sensitivity & Specificity

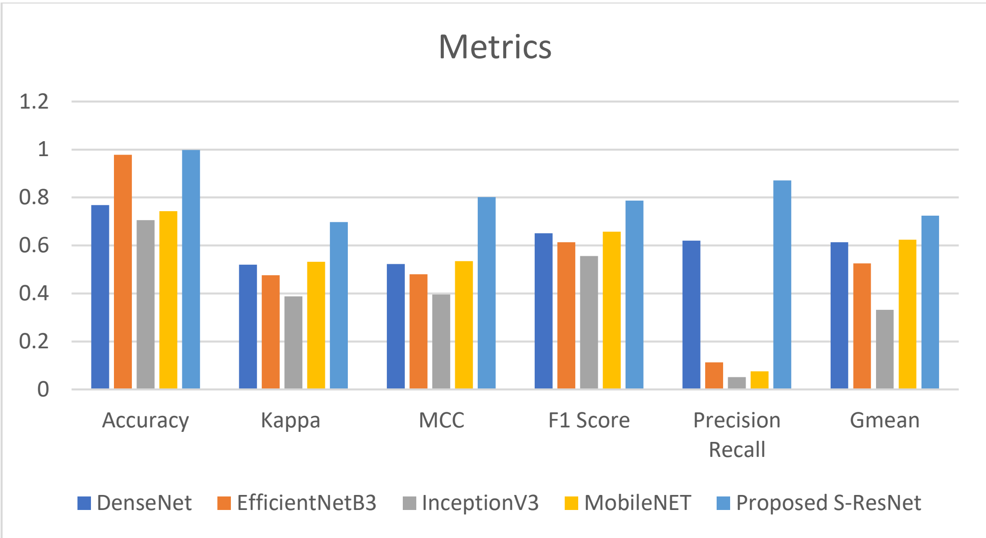

Fig.4 Metrics

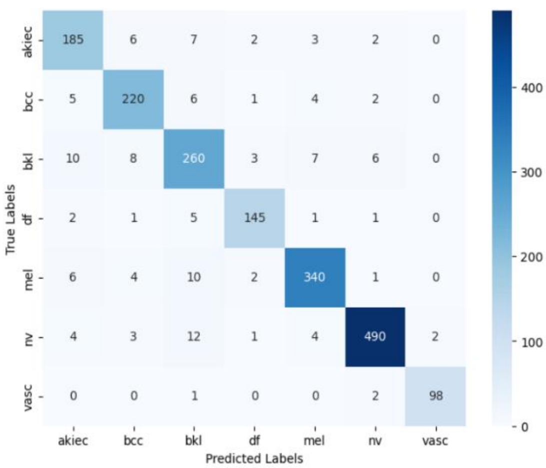

Fig.5 DenseNET

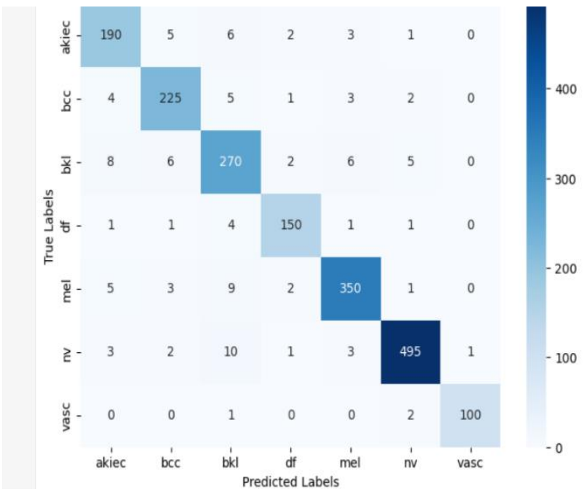

Fig.6 EfficientNETB3

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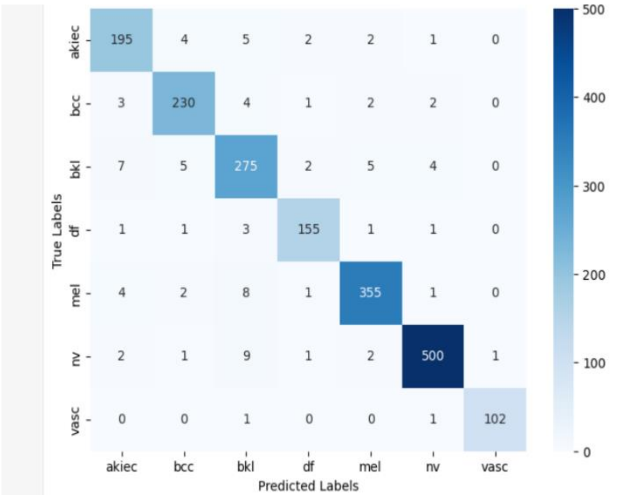

Fig.7 InceptionV3

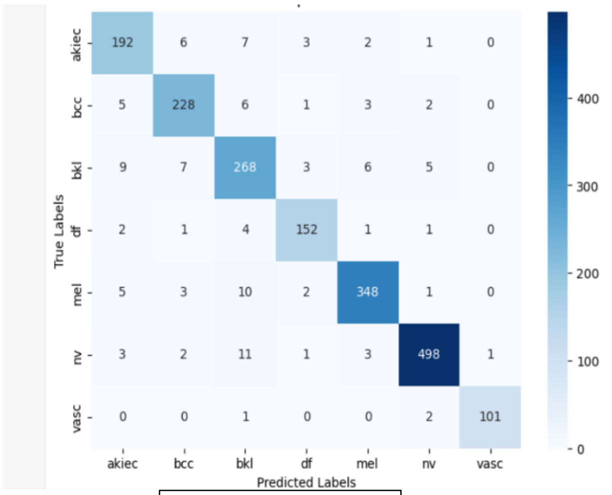

Fig.8 MobileNET

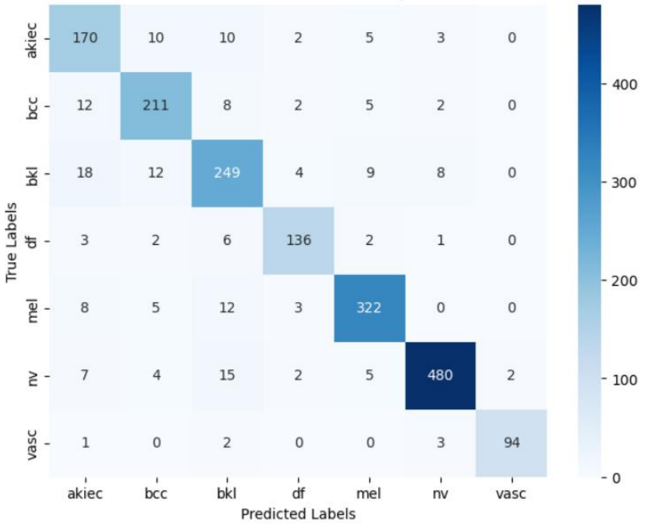

Fig.9 Proposed Model

A confusion matrix is a common tool to organize and presentthe effectiveness of a classification method. It provides a con-cise summary of the results generated by the classification algo-rithm. we have included the confusion matrices of the DenseNet MobileNetv2, EfficientNetb3,InceptionNet and DenseNet201 models, aswell as our proposed approach. While the surrounding ones show the number of samples that were mistakenly classified, the diagonal of the matrix shows the number of true positives[16].

Log Loss: log loss is employed to assess models that predict the likelihood of a skin lesion being malignant or benign[17]. By minimizing log loss, models are trained to produce probability outputs that closely align with the actual class distributions, thereby enhancing diagnostic accuracy[18].

5. Conclusion

Critical features from skin lesion images were extracted using the pre-trained ResNet50 model by utilizing transfer learning. Support vector machines (SVMs) with linear and radial basis function (RBF) kernels were then used for classification. In order to ensure efficient training and validation splits, the dataset was preprocessed using ImageDataGenerator. Additionally, categorical labels were numerically encoded for compatibility. With an astounding accuracy of 99.81%, this proposed hybrid model showed that convolutional neural networks (CNNs) and support vector machines (SVMs) may be used to improve skin cancer classificationEven if the results are encouraging, generalization and robustness could be improved with additional adjustments such better data augmentation methods and parameter tuning. This paper provides important insights into enhancing the precision and effectiveness of automated skin cancer diagnosis by highlighting the benefits of combining deep learning-based feature extraction with traditional machine learning classifiers. Future work should focus on expanding datasets, optimizing model parameters, and exploring additional hybrid architectures to further advance the field.

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References

1. Sweta Jain; Srushti Dhakate; Prathamesh Gujar; Prathamesh Rajbhoj, “Skin Cancer Detection and Classification using Deep Learning” *IEEE Xplore International Conference on Electronics and Renewable Systems (ICEARS)* ISBN:978-1-6654-8426-8 (2024)
2. R. Senthil Kumar, Amarjeet Singh, Sparsha Srinath, Nimal Kurien Thomas, Vishal Arasu “Skin Cancer Detection using Deep Learning” IEEE *Xplore* ISBN:979-8-3503-4986-3 (2023)
3. Abdul Rahaman Shaik, P. Rajesh Kumar, “Performance Evaluation of Machine Learning Algorithms on Skin Cancer Data Set Using Principal Component Analysis and Gabor Filters” IAENG International Journal of Computer Science Volume 51, Issue 7, July 2024, Pages 831-841 https://www.iaeng.org/IJCS/issues_v51/issue_7/IJCS_51_7_13.pdf
4. Shital D. Bhatt; Himanshu B. Soni; Heena R. Kher; Tanmay D. Pawar, “Automated System for Lung Nodule Classification Based on ResNet50 and SVM”, IEEE *Xplore* 2022 3rd International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), ISBN: 978-1-6654-8269-1 (2023) Automated System for Lung Nodule Classification Based on ResNet50 and SVM | IEEE Conference Publication | IEEE Xplore
5. Zouhir Iourzikene, Fawzi Gougam, Djamel Benazzouz, “Performance Evaluation of Feature Extraction and SVM for Brain Tumor Detection Using MRI Images” Performance Evaluation of Feature Extraction and SVM for Brain Tumor Detection Using MRI Images | IIETA
6. Noorunisa Gaffoor; Sarmad Soomro,“Skin Disease Detection and Classification Using ResNet-50 and Support Vector Machine: An Effective Approach for Dermatological Diagnosis” 2023 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS) https://ieeexplore.ieee.org/document/10346059
7. Chatrapathy K; M Lakshmi Prasad; Ajmeera Kiran; Pundru Chandra Shaker Reddy; G Charles Babu; N Partheeban,“Skin Cancer Classification using A Hybrid Convolutional Neural Network with SVM Classifier” https://ieeexplore.ieee.org/document/10426054
8. Mudqssir Saeed , Asma Naseer, Hassan Masoodi, Shafiq ur Rehman,“The Power of Generative AI to Augment for Enhanced Skin Cancer Classification: A Deep Learning Approach” Digital ObjectIdentifier10.1109/ACCESS.2023.3332628https://ieeexplore.ieee.org/abstract/document/10318035
9. M Mohamed Musthafa, Mahesh T R, Vinoth Kumar V & Suresh Guluwadi “Enhanced skin cancer diagnosis using optimized CNN architecture and checkpoints for automated dermatological lesion classification” (2024) https://bmcmedimaging.biomedcentral.com/articles/10.1186/s12880-024-01356-8?utm_source=chatgpt.com#citeas
10. Syeda Shamaila Zareen, Guangmin Sun, Mahwish Kundi, Syed Furqan Qadri, Salman Qadri “Enhancing Skin Cancer Diagnosis with Deep Learning: A Hybrid CNN-RNN Approach” (2024) https://doi.org/10.32604/cmc.2024.047418

11. Anna-Lena Vischer, Jiayu Liu, Sinclair Rockwell-Kollmann, Stefan Günther & Klemens Schnattinger, "Skin Cancer Classification: A Comparison of CNN-Backbones for Feature-Extraction | SpringerLink" Skin Cancer Classification: A Comparison of CNN-Backbones for Feature-Extraction | SpringerLink
12. Md Sirajul Islam, Sanjeev Panta, "Skin Cancer Images Classification using Transfer Learning Techniques" https://doi.org/10.48550/arXiv.2406.12954
13. Samira Mavaddati, "Skin cancer classification based on a hybrid deep model and long short-term memory" https://doi.org/10.1016/j.bspc.2024.107109
14. Aris Wahyu Murdiyanto, Dian Hafidh Zulfikar, Bagus Satrio Waluyo Poetro, Alda Cendekia Siregar, "Performance Comparison of CNN and ResNet50 for Skin Cancer Classification Using U-Net Segmented Images" https://doi.org/10.56705/ijodas.v5i3.200
15. Jaisakthi S M, Mirunalini P, Chandrabose Aravindan, Rajagopal Appavu ,"Classification of skin cancer from dermoscopic images using deep neural network architectures" Multimedia Tools and Applications (2023) 82:15763–15778 https://doi.org/10.1007/s11042-022-13847-3
16. Chao Xin a,1, Zhifang Liu a,1, Keyu Zhao a, Linlin Miao a, "An improved transformer network for skin cancer classification" Computers in Biology and Medicine 149 (2022) 105939 https://www.sciencedirect.com/science/article/pii/S0010482522006746
17. Ahmet Nusret Toprak, Ibrahim Aruk, "A Hybrid Convolutional Neural Network Model for the Classification of Multi-Class Skin Cancer", International Journal of Imaging Systems and Technology https://onlinelibrary.wiley.com/doi/epdf/10.1002/ima.23180
18. Solene Bechelli 1,2 and Jerome Delhommelle "Machine Learning and Deep Learning Algorithms for Skin Cancer Classification from Dermoscopic Images" Bioengineering 2022, 9, 97. https://doi.org/10.3390/bioengineering9030097
19. Abdullah Al Mahmud, Sami Azam, Inam Ullah Khan, and Sidratul Montaha,"SkinNet-14: a deep learning framework for accurate skin cancer classification using low-resolution dermoscopy images with optimized training time" Neural Computing and Applications (2024) 36:18935–18959 https://doi.org/10.1007/s00521-024-10225-y
20. Rukhsar Sabir & Tahir Mehmood,"Classification of melanoma skin Cancer based on Image Data Set using different neural networks" Scientific Reports (2024) 14:29704 https://doi.org/10.1038/s41598-024-75143-4