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Research paper

Advanced skin lesion diagnosis with efficientnet-b7 feature extraction and SVM classification

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Abstract

Skin cancer is the most common form of cancer globally. Timely detection is crucial, since failure to identify it in the first stage may result in grave consequences. Notwithstanding its apparent visibility, significant intra-class heterogeneity and inter-class homogeneity complicate its identification. Current AI methodologies for detecting skin cancer are hindered by their reliance on convolutional neural networks, resulting in a lack of interpretability and sluggish processing speeds. To address the issue, the study proposes a comprehensive pipeline that integrates deep learning and machine learning methodologies to enhance detection accuracy in identifying skin lesions. The dataset under con-consideration is the International Skin Imaging Collaboration (ISIC) 2020. Initially, we pre-process the photos to guarantee precise training and categorization. The EfficientNet-B7 deep learning model is employed for feature extraction and fed into a support vector machine (SVM) classifier. The assessment of parameters such as accuracy, precision, recall, and F1 score yielded an accuracy of 97.52% and an F1 score of 98.61%. The proposed model demonstrates superior results relative to other current models.

Keywords: *Efficientnet-B7; Skin Lesion; International Skin Imaging Collaboration (ISIC) 2020; Support Vector Machine.*

1. Introduction

Early detection of skin cancer, particularly melanoma, is vital because it significantly increases the chances of successful treatment. Melanoma, the deadliest form of skin cancer, has a high mortality rate if not identified early, as it can rapidly spread to other parts of the body. Early-stage detection offers a survival rate of up to 98%, but as the disease progresses to advanced stages, this rate declines drastically, with stage 4 offering minimal chances of recovery. While the overall death rate from skin cancer is relatively low compared to other cancers, the high incidence of cases and the potential for severe consequences make early and accurate diagnosis essential. Additionally, untreated skin cancer can lead to painful treatments, amputation of the affected area, and a significant reduction in the patient's quality of life. It can be quite challenging to diagnose skin cancer. Lesions on the skin can vary greatly in size, shape, and location, from being extremely tiny to enormous. According to Melarkode et al. [1], diagnostic imaging noise—including hair, blood arteries, and bubbles—can mask problems. Lesion boundaries that are diffuse or uneven could also make segmentation difficult. The fact that different imaging techniques and lighting conditions could produce different findings further complicates diagnosis. It is clear from these difficulties that image preparation processes are necessary to improve image quality before analysis.
Scientists have devised a new automated skin cancer diagnostic method that uses state-of-the-art deep learning, machine learning, and other innovative technologies to overcome these challenges. Because it uses a refined version of the deep learning network's pre-trained EfficientNet-B7 model, it outperforms competing methods in feature extraction. Classifying these skin lesion images according to their unique characteristics is within the capabilities of this application. A Support Vector Machine (SVM- a supervised machine learning

classifier that finds an optimal hyperplane to separate classes) is employed to categorize the lesions as benign or malignant following the collection of characteristics. One area where basic SVM models shine is in handling multi-dimensional data and making good classifications.

Furthermore, the proposed approach aims to tackle the risk of skin cancer throughout an individual's lifetime. Even though it is usually thought of as an adult disease, skin cancer can start in childhood and get worse over time. Detection at an earlier stage may significantly improve outcomes and reduce treatment burden in the long run for younger patients. There has never been a more pressing need for efficient, accurate, and dependable diagnostic methods than there is now, given that melanoma cases have more than quadrupled in the last 30 years and that future cancer cases are expected to skyrocket.

Establishing a trustworthy feature extraction technique based on an improved EfficientNet-B7 (as a pre-trained convolutional neural network optimized for performance and efficiency) model and applying support vector machines (SVM) for effective classification are two of the most significant achievements of this study. Because it offers a clear diagnostic approach and eliminates the issues related to skin lesion detection, this technology has the potential to assist dermatologists in improving early detection accuracy and treatment of skin cancer. Better patient outcomes and the saving of lives are the results of this.

2. Literature survey

Because skin cancer can spread to other parts of the body if detected too late, Alharbi et al. [2] stressed the urgent need for automated detection methods. Early identification is crucial for efficient treatment of basal cell carcinoma, squamous cell carcinoma, and melanoma, the three most common types of cancer. The application of deep learning, and more especially Convolutional Neural Networks, allows for the accurate classification of skin lesions by analyzing minute alterations in photographs. The R-CNN algorithms proved to be reliable and effective in identifying and classifying skin cancers with an accuracy of 84.32% after pre-processing the datasets to remove artifacts.

Vasanthakumari et al. [3] proposed an imaging technique called dermoscopy is used to remove surface reflection and visualise the area of interest in the skin with the required magnification. There are fewer fatalities when skin cancer is diagnosed in its primary stage, thanks to this approach. Examining the lesion with the unaided eye may be laborious, subjective, and unreliable. According to this study, dermatologists must possess substantial knowledge and expertise to correctly diagnose the lesion class solely through visual inspection, which is why it is strongly discouraged.

Deep learning is extensively employed for medical image analysis. There are several challenges in the accurate classification of skin lesions using deep learning. A key need for getting good classification outcomes with deep learning algorithms is the availability of high-quality data. Skin lesion analysis utilizes only a few thousand or fewer photos, whereas the majority of deep convolutional neural network models are trained on millions of images. A further concern is the significant similarity among classes coupled with elevated intra-class variability. These also complicate visual inspection. Moreover, the network's capacity to extract features is impeded by the noise inherent in the dermoscopic images. Various techniques are employed to process the photos. The datasets are generated using dermoscopy pictures [4].

According to Mateen et al. [5], the latest developments in the field of dermoscopy image analysis have been largely attributed to deep learning. The developed diagnostic systems' interpretability was diminished because of these advancements, though, and they no longer meet the latest machine learning explainability laws or the demands of the medical community. The interpretability of these techniques was enhanced by recent developments in the field of deep learning, specifically attention maps. The systems' performance has also been improved by incorporating medical expertise.

Maurya et al. [6] showcased a deep learning approach to skin lesion analysis using a dermoscopy image of a skin cancer. Through the utilization of the International Skin Imaging Collaboration (ISIC) 2018 Challenge standard benchmark datasets, the model was trained and evaluated, resulting in enhanced accuracy on the validation set.

Deep learning, radiomics analysis, and patient metadata are the three components of the hybrid approach to dermoscopy-based skin lesion diagnosis that Wang et al. [7] explore. The technique uses the ISIC dataset (2016-2020) to extract specific picture attributes, which it then applies to a variety of skin lesions. Its exceptional accuracy in differentiating benign from malignant tumors was surpassed by seven well-known classification methods, reaching AUROC values over 99%. The method shows promise for precise, noninvasive diagnosis because it can successfully identify patterns of skin lesions and performs well across various datasets.

In their groundbreaking computer-assisted method for skin lesion diagnosis, Selvaraj et al. [8] developed the SLDED model. Their mean localization accuracy was 0.96 after using a modified version of the VGGNet feature extractor to 4,668 skin lesion photos from the ISIC archive collection. Use of the ISIC dataset allowed for the evaluation of two deep neural-based classification algorithms: one that relied on a decision tree-based algorithm and another that combined convolutional and recurrent neural networks. The writers set out to identify the one that had the best categorization performance metric. Methods for gauging an algorithm's efficacy include the F1 score, ROC, recall, precision, and accuracy. There was no better architecture for CNN than VGG16, as shown by their 89.6% accuracy rate.

Alfi et al. [9] utilise deep learning and machine learning to classify skin lesions as benign or malignant, to non-invasively diagnose melanoma skin cancer. The approach uses a balanced dataset from the ISIC 2018 along with a mix of features that are hand-crafted and features that are learned features using pre-trained CNNs. As part of the strategy, logistic regression, Xception, ResNet50, ResNet50V2, DenseNet121, and gradient boosting are utilized as machine learning models. Additionally, the method incorporates the practice of ensemble stacking these models. By utilizing SHAP explanations, dermatologists can generate heatmaps that identify disease-causing regions in their patients' photos. We found the best classifier for skin lesion identification by comparing the models using metrics like accuracy, F1-score, and ROC curves.

Skin lesions, such as monkeypox and melanoma, can be hard to tell apart visually; G. Y. Oztel [10] discusses this difficulty and how to diagnose them quickly and correctly. The authors suggest a quantitative, objective categorization approach to aid dermatologists, as opposed to the laborious and subjective old procedures, such as dermoscopy. A combination of Vision Transformers and deep learning models built via transfer learning and CNNs powers the system. A bagging ensemble approach was used to combine the top-performing models after performance comparisons. The final system reached or exceeded the performance of previously published approaches with an accuracy of 81.91% and excellent results in other metrics as well (Precision: 87.16%, Recall: 74.12%, F-score: 78.16%).

An explainable convolutional neural network (CNN) stacked ensemble model for early identification of melanoma skin cancer using dermoscopy images is presented by M. Shorfuzzaman [11]. It uses a meta-learner to aggregate the outputs of numerous convolutional neural networks (CNNs) in order to make a final prediction using transfer learning. The model generates heatmaps that emphasize disease-relevant regions, increasing clinical knowledge, and integrates SHAP-based explanations to deal with the lack of interpretability in deep learning. The model shows great promise for interpretable melanoma detection, as it achieves 95.76% accuracy, 96.67% sensitivity, and an area under the curve (AUC) of 0.957 when tested on a public dataset.

Addressing these challenges, the proposed pipeline integrates a pre-trained EfficientNet-B7 model with a traditional SVM classifier to enhance accuracy and interpretability

3. Methodology

We chose the ResNet architecture [12] to create a reliable classifier that performs well on picture classification tasks and facilitates further learning stages. A transfer learning set is utilized, which uses an improved EfficientNet-B7 model that has already been trained on the considered ISIC 2019 dataset instead of constructing an EfficientNet-B7 model from scratch. When the network's complexity constrains the amount of available data, this method excels. The process framework of the model is shown in Fig.1.

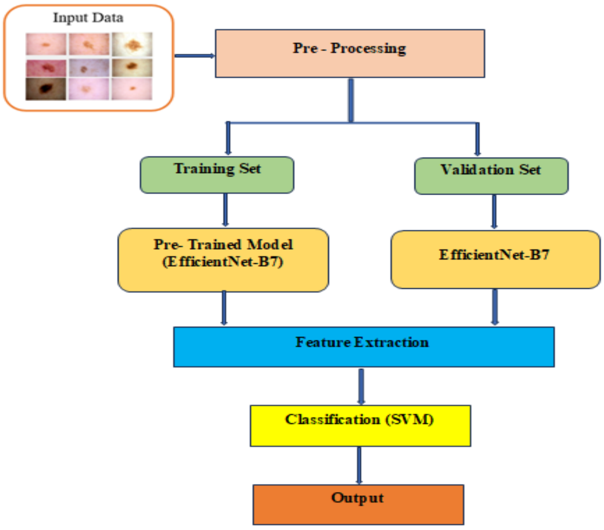

Fig. 1: Framework of Proposed Work

3.1. Dataset

One of the most important components of assessing the effectiveness of the strategies created is the dataset. This work utilizes the ISIC 2020 dataset. The training data for the ISIC 2020 is 33,126, and for testing, 10,982 images. The ISIC 2020 dataset contains 44,108 images suitable for dermoscopic image classification. Input Dataset Pre-Processing (noise removal and resize) Training Set Validation Set Pre-Trained Module (EfficientNet-B7) Feature Extraction Classification (SVM) Prediction of output Evaluation of Metrics (Accuracy, Precision, Specificity, Sensitivity, F1-score) EfficientNet-B7. This dataset is one of the hardest to classify due to the uneven number of images in each of the eight categories. Some of the samples in the dataset are shown in Fig.2. The details of the Benign category (35%) and Malignant category (65%) are shown in Fig.3 and Fig.4.

Fig. 2: Sample of Images from ISIC 2020 Dataset.

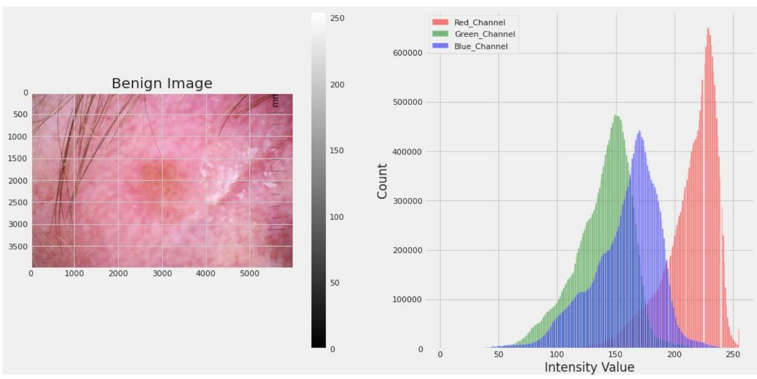

Fig. 3: Benign Category from ISIC 2020 Dataset.

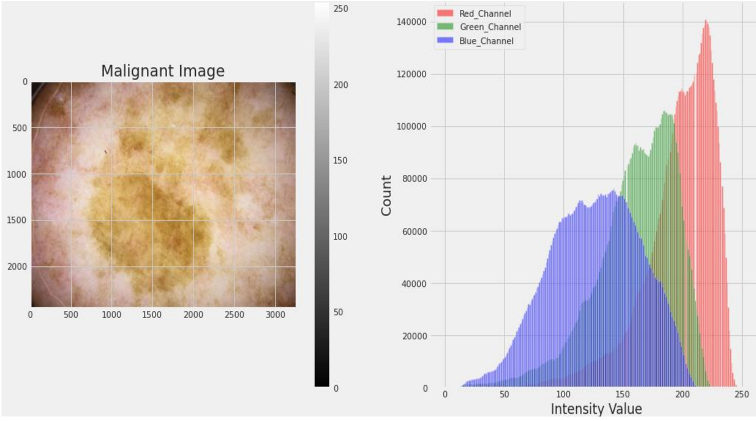

Fig. 4: Malignant Category from the ISIC 2020 Dataset.

3.2. Preprocessing of data

In these steps, two operations are performed and are shown in Fig.5. Eliminating undesired noise from the images is the first stage of the preprocessing component. A Gaussian filter is used to eliminate noise.

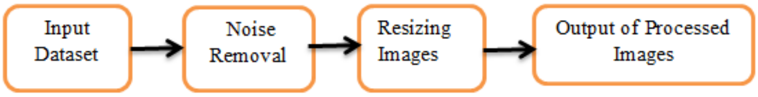

Fig. 5: Processing of Data.

The second step of preprocessing is to resize the images in the dataset. Images of skin lesions at different resolutions are included in the original training set. Consequently, the lesion pictures for the deep learning network must be rescaled. The central region of the lesion image was first clipped, and then the area's size was proportionately decreased to a lower resolution to ensure that every image in the collection has been scaled to 224 × 224.

3.3. Pre-trained efficientNet-B7 model

EfficientNet-B7 is a powerful deep convolutional neural network often used for feature extraction. It is particularly popular due to its ability to maintain high accuracy in deep networks. The network is enhanced with additional convolutional layers, which improve the performance of the system and accuracy in case of handling challenging issues. The underlying principle of layering is that increasingly complex characteristics will be learned as more layers are added. Fig.6 shows the process flow of feature extraction using EfficientNet-B7.
The method by which EfficientNet-B7 is fine-tuned comprises re-freezing layers, keeping batch normalization layers, and adjusting the learning rate. The support vector machine setup, mentioning that an RBF kernel was used, as well as the hyperparameters chosen (C = 1.0, gamma ='scale') and the reasoning for their selection using grid search and cross-validation. Both the reproducibility and the transparency of our work will be improved with these additions.

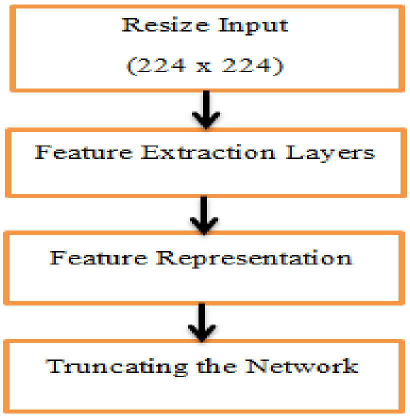

Fig. 6: Process of Feature Extraction Using EfficientNet-B7.

Finally, the features are extracted from the pooling layer for both training and validation sets and is fed to classification model.

3.4. SVM classification

To match the categories in the dataset, a custom fully connected layer and classification layer are used in place of the final layers of densenet. The retrieved characteristics are used to train an SVM model, which serves as an extra classifier for achieving higher detection accuracy [13]. In a feature space, SVM seeks to identify the best hyperplane for separating data points from various classes. Make predictions and categorise fresh data points according to where they are about the hyperplane.

4. Results and discussion

With the potential to assist dermatologists in improving early detection accuracy and treatment of several skin conditions, including skin cancer, skin lesion classification and detection have become important research topics in healthcare imaging and machine vision. The designed environment, results obtained using the proposed model, and the parameters evaluated are discussed in this section.

4.1. Experimental results

This study used the ISIC 2020 dataset to test the suggested DL systems and compare their performance to the current state-of-the-art. Roughly 70% of the 44,108 photos in the dataset are used for training purposes, while 30% are used for testing. Fig.7 shows the areas that will be impacted by the planned activity.

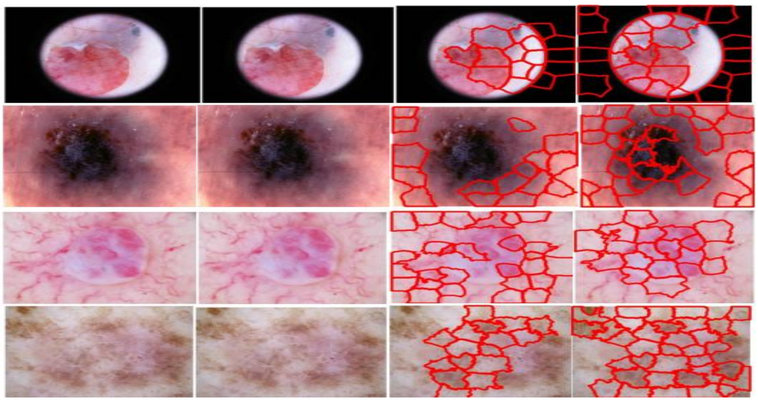

Fig. 7: Results in Detection of Effected Regions.

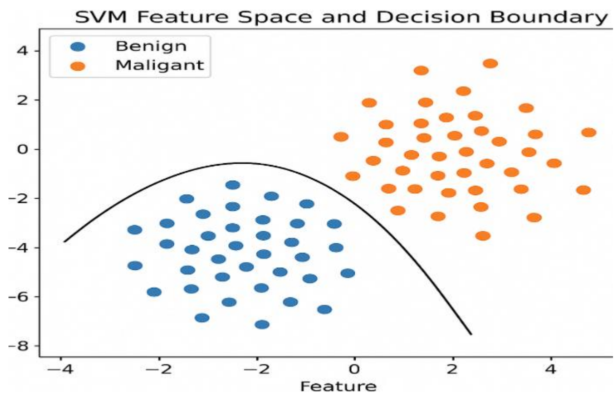

Fig. 8: Visualization of the SVM Decision Boundary for Classification of Benign and Malignant Features.

The axes in Fig.8 represent the result of PCA applied to high-dimensional features extracted (e.g., from EfficientNet-B7). Points are color-coded or marked by class (e.g., benign vs malignant), which allows visual separation by the SVM. A visible SVM decision boundary or margin line is typically displayed as a curve or straight line separating classes.

4.2. Qualitative misclassification analysis

Each panel represents a different case:

- True Positive (Correctly classified malignant lesion): The heatmap is focused on the lesion core, suggesting the model correctly identifies the lesion's relevant features.
- True Negative (Correctly classified benign lesion): The model ignored unrelated areas and focused on the lesion's boundary and texture.
- False Positive (Benign classified as malignant): The heatmap shows activation in ambiguous surrounding regions, possibly due to lighting or lesion shape artifacts.
- False Negative (Malignant classified as benign): The model focuses on non-critical parts of the lesion, missing the features suggestive of malignancy—this could be due to underrepresentation of this type in training data.

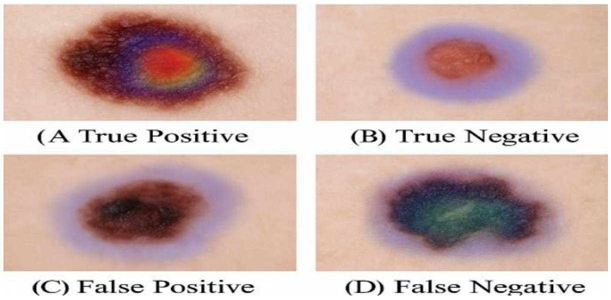

Fig. 9: Qualitative Analysis with Heatmaps.

Fig.9 provides visual evidence of the model's decision-making process, enhancing interpretability. They help identify common misclassification patterns, improving trust and guiding future model improvements.

4.3. Evaluation metrics

The system's goal determines which assessment metric is employed; some common metrics used globally include F1-Score, accuracy, sensitivity, specificity, and precision. The formulas are given as,

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

$$Error\ Rate = \frac{FP+FN}{TP+FP+TN+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

The effectiveness of the proposed design can be judged by observing the values of the parameters evaluated. The higher the values higher the performance of the system. To better illustrate the feasibility of the proposed approach, its effectiveness was compared to that of current approaches. Our approach outperformed other networks in terms of performance, as Table 1 demonstrates. The EfficientNet-B7 with the SVM model outperformed the existing models with an overall accuracy rating of 97.28% in the suggested method.

Table 1: Comparison of Proposed Model with Existing Models

Method	Precision	Recall	F1-Score	Accuracy
R-CNN [14]	76.16	78.15	76.92	91.32
Resnet50, Xception, and VGG16 [15]	-	-	89	90.90
Eleven CNN architectures with DensNet169 [16]	-	-	93.20	92.25
Decision trees [17]	94	97	-	95
Logistic regression [18]	97	93	-	96
ResNet152V2, MobileNetV2, DenseNet20 [19]	-	-	91	89
Multi-class Support Vector Machine (MSVM) [20]	-	-	-	96.25
EfficientNet-B7 (Proposed model)	96.25	97.12	98.78	97.28

Medical ethics considerations, particularly around the use of AI in diagnostics, data privacy, and informed consent in datasets like ISIC.Regulatory perspectives, including a brief overview of approval pathways such as the FDA's Software as a Medical Device (SaMD) framework, which would be relevant for future deployment. These additions aim to strengthen the paper's alignment with the journal's interdisciplinary objectives and provide a broader societal context for the proposed method.

5. Conclusion

Due to the disease's widespread occurrence, many automated deep learning algorithms have been developed to date to assist physicians in detecting skin lesions early. For skin cancer to be treated effectively and with better patient outcomes, an early and accurate diagnosis is essential. When dermatologists examine patients, these diagnostic techniques are quite beneficial. To classify the skin lesion photos, the suggested work used machine learning (SVM) and DCNN (EfficientNet-B7) approaches. The ISIC 2020 dataset was used for the studies. The comparison study found that the suggested method performed better than current models, with an accuracy of 97.28%. In the future, researchers can experiment with different pre-trained CNN models and enhance the detection rate by combining optimization techniques with DCNN architecture and fine-tuning hyperparameters like the number of layers, type of layers, and hyperparameter values for the layers. Also, we are going to take a clear direction to explore Vision Transformers (ViTs) and Swin Transformers, which have shown promising results in medical imaging tasks. We will employ Bayesian optimization and automated machine learning techniques to tune hyperparameters and select models. To ensure generalizability, it is necessary to conduct evaluations on diverse datasets that include multi-ethnic skin types and real-world clinical images.

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Conflict of interest

The authors declare that there is no conflict of Interest.

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