SVM-RF-CNN Gradient Boosting Ensemble Learning for Skin Cancer Detection

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Abstract:

Skin cancer is cancer that starts as a growing of cell on the skin. The cell can invade and destroy health and destroy healthy body. Skin cancer is one of the most common and life-threatening diseases. Early diagnosis and treatment of skin cancer depend on its detection. For precise skin cancer prediction, this study offers a hybrid classification method that combines deep learning and conventional machine learning models. Through the integration of cutting-edge machine learning algorithms, this project suggests a reliable and accurate skin cancer categorization system. Preprocessing operations including scaling, RGB conversion, and input image normalization are the first things the system does. EfficientNetB3 and ResNet50 models that have already been trained are used to extract features. SelectKBest with mutual information is used for feature selection in order to improve model performance. Three models are used to classify the chosen features: a shallow Convolutional.Neural.Network(C N N),Random Forest, and Support Vector Machine (S V M). The final prediction is created by combining their outputs using a Gradient Boosting ensemble. Dermatologists may find this integrated approach useful in clinical decision-making since it increases classification accuracy and facilitates accurate skin cancer detection.

Keywords: Machine Learning, Scaling, Image Normalization, Support Vector Machine, Random Forest, Convolutional.Neural.Network

Introduction

1.1. Motivations

Since skin cancer is a prevalent and dangerous condition,early identification is essential. for both survival and efficient therapy. Conventional methods of skin cancer diagnosis can be laborious and overly rely on medical expertise. This can occasionally result in errors or hold-ups. A faster and more accurate method of examining skin photographs is provided by machine learning (ML). It may identify patterns in the pictures that are difficult for people to notice. In areas with a shortage of medical professionals, using an ML-based approach can help physicians identify skin cancer earlier, make fewer mistakes, and provide care to more individuals.

1.2. Objectives

- Early Detection Using ML & Image Processing: Create a technology that employs image processing and machine learning to analyze lesion photos and identify skin cancer early in order to increase survival rates and treatment results.
- Binary Classification of Lesions: Assign benign or malignant classifications to lesions in order to facilitate prompt clinical judgments and evaluate the risk and urgency of treatment.
- Use of Multiple ML Models: Apply and assess CNN, SVM, and Random Forest models to accurately classify skin lesions using image characteristics.
- Feature Selection & Extraction: Choose pertinent characteristics and cut down on noise in dermoscopic pictures to improve model accuracy.
- Ensemble Learning for Increased Accuracy: To improve prediction dependability and system performance, combine CNN, SVM, and RF outputs using gradient boosting.

1.3. Original Contributions

This project's unique blend of cutting-edge tools for precise skin cancer classification is its original contribution. For deep feature extraction from dermoscopic pictures, we employ ResNet50 and EfficientNetB3, which capture both intricate and subtle features. SelectKBest with mutual information is used to choose the most pertinent characteristics in order to improve model performance. Ultimately, a soft voting method is used to combine Support Vector Machine (SVM), Random Forest, and Convolutional Neural Network (C N N) models in an ensemble learning strategy. The overall accuracy, dependability, and robustness of skin cancer detection are greatly increased by this integration of feature extraction, selection, and ensemble classification.

1.4. Paper Layout

This is how the remainder of the paper is structured: A review of relevant works is provided in Section 2, the suggested model is explained in Section 3, the experiments and their outcomes are described in Section 4, and future work and advancements are covered in Section 5.

2. Literature Survey

One of the most prevalent human diseases is skin disease. Skin cancer is a tumor (growth of atypical cells on the skin) in your body’s organ. Thes skin tumor are two type, that are malignant (Cancer) and benign (Noncancer). Certain forms of skin cancer may manifest as rough patches, wart-like growths, or reddish or blackish areas. It's critical to recognize these symptoms and routinely examine your skin for any changes because early detection is essential. Skin color is a powerful indicator of this condition in computer vision applications. This approach uses pictures of the skin to identify skin cancer[1] . A paragraph about the importance and difficulties of detecting dermatological conditions in the twenty-first century is included in the image. It highlights the difficulty and expense of diagnosing skin conditions, which are frequently complicated by the arbitrary judgment of human specialists. It specifically draws attention to melanoma, a skin cancer that can be lethal, and emphasizes how crucial early detection is to better treatment results. In order to improve early diagnosis and lessen dependency on manual evaluations, the text promotes the use of automated diagnostic techniques utilizing image-based analysis[2] . The main causes of skin cancer include bad lifestyle choices, UV rays, and air pollution. Machine learning will be utilized to identify the illness and assist us in identifying the outcome[3] . A thorough machine learning-based system for the use of dermoscopic pictures in the diagnosis of skin cancer was presented by Murugan et al. in 2021. In order to isolate the region of interest (ROI), they first segmented the images using the Mean Shift method after pre-processing them with a median filter to remove noise like hair and bubbles. They used three techniques for feature extraction: The texture and form of skin patches were captured by the study using characteristics such as Moment Invariants, GLRLM, and GLCM. In order to aid in the identification of skin lesions, it concentrated on color, texture, form, and size. Classification was then done using these characteristics. To determine the most effective method of detecting skin cancer, several models were examined, such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Neural Networks with Backpropagation. Because of its layered architecture that replicates visual perception, CNNs—which are renowned for their capacity to manage spatial hierarchies in picture data—showed strong performance among these. The research demonstrates a distinct progression from human diagnosis to semi-automatic techniques and, more recently, automated diagnostic systems based on deep learning. Enhancing model reliability, cutting down on diagnostic time, and facilitating extensive screenings with open datasets like ISIC continue to be the major priorities. In order to obtain high accuracy in melanoma diagnosis, Vijayalakshmi's approach combines strong pre-processing, a variety of segmentation techniques, and potent classifiers[2].

The importance of incorporating preprocessing, segmentation, and robust classification into melanoma detection procedures is reaffirmed by this literature. Additionally, it encourages the continuous development of machine learning techniques in dermatology with the goal of enhancing therapeutic results via automated and early diagnosis[3].

Building on these discoveries, our project combines CNN, Random Forest, and SVM and leverages Ensemble Learning with Soft Voting to further increase prediction performance in terms of accuracy and dependability.

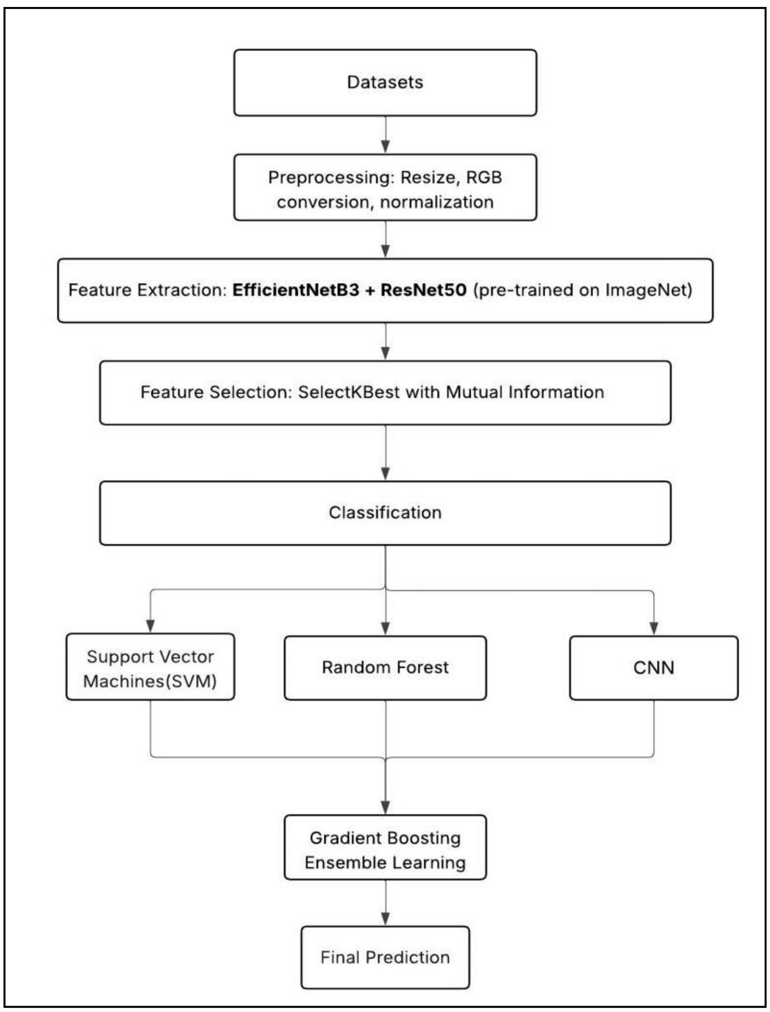
3. Proposed System/Model

In order to identify skin cancer, our project will first process an image of the skin before applying both conventional advanced deep learning methods and machine learning methods. First, the dataset is gathered; next, the images are preprocessed to prepare them for analysis; third, the most significant features are extracted and chosen from the images; fourth, machine learning models are used to classify the image as either cancerous or non-cancerous; and fifth, ensemble learning is used to aggregate the output from various models to improve the final prediction's accuracy and dependability.

3.1. Methodologies Used

a. Data Collection: Skin Cancer: Malignant vs. Benign
b. Preparation: RGB conversion is used to provide uniform color channels,by scaling pixel values, normalization enhances model performance.
c. Extraction of Features: EfficientNetB3 and ResNet50, both trained on ImageNet.
d. Feature Selection:
    i. The most pertinent attributes are selected using SelectKBest.
    ii. Each feature's significance in relation to the target label is assessed using Mutual Information as the scoring function.
e. Classification:
    i. Support Vector Machine(S V M)
    ii. Random Forest
    iii. Convolutional Neural Network (C N N)
f. Ensemble Learning: The predictions of the three classifiers are combined using a Gradient Boosting Ensemble technique.

3.2. Schematic Layout of the Proposed System/Model



[Fig-1: SVM-RF-CNN Gradient Boosting Model]

- Data Collection: A range of skin lesion photos are included in the dataset "Skin Cancer: Malignant vs. Benign" that was used for this project. Both benign (non-cancerous) and malignant (cancerous) examples are depicted in these pictures. The dataset is perfect for supervised learning because it is well-labeled and publically accessible. It serves as the basis for model evaluation and training, allowing the system to reliably differentiate between the two kinds.
- Preparation: Image preprocessing guarantees that all inputs are appropriate for feature extraction and consistent. The color channels of the pictures are standardized using RGB conversion. After that, pixel values are scaled, usually between 0 and 1, to apply normalization. By lessening the effect of lighting changes and ensuring quicker convergence during training, this step improves model performance.
- Extraction of Features: Two pre-trained convolutional neural networks, ResNet50 and EfficientNetB3, which were both trained on the ImageNet dataset, are used to extract features. From the skin lesion photos, these deep learning models can extract intricate and sophisticated information. When combined, they produce a rich feature representation that greatly enhances the classification work and is more informative than raw image pixels.
- Feature Selection:

  To hone in on the most instructive aspects and keep the rest:
  1. SelectKBest: This technique reduces the dataset to just the most pertinent variables by choosing the best features based on statistical scores.
  2. Mutual Information: This scoring mechanism assesses the relative contribution of each characteristic to the target label prediction. By doing this, unnecessary or redundant characteristics are removed, increasing the accuracy and efficiency of the model.
- Classification:

  Three distinct models are used to classify the chosen features.
  1. Support Vector Machine (SVM): Effective in binary classification problems and efficient in high-dimensional areas.
  2. Random Forest: A strong decision tree ensemble that minimizes overfitting and manages noisy data.
  3. Convolutional Neural Network (CNN): Superb at recognizing visual patterns and learning the spatial hierarchies of features from the input images.
- Ensemble Learning:

  A stacked ensemble approach is used to improve performance even further. The CNN, Random Forest, and SVM models' probability outputs are first gathered and utilized as input features for a meta-classifier, in this case a Gradient Boosting Classifier. The outputs of the several base models are combined in the most effective way by this meta-model. This ensemble approach greatly increases overall classification accuracy and reliability in skin cancer prediction by utilizing each model's strengths and mitigating its unique shortcomings.

3.3. System Requirements

- Software: Jupyter Lab, Python 3.10, TensorFlow, Keras, Scikit-learn
- Hardware: Intel i5 or higher, 8+ GB RAM

3.4. Proposed Agorithm(s)

- Support Vector Machine (SVM):
  a. SVM using an RBF (Radial Basis Function) kernel, which excels at processing complex, non-linear data, is used in this project.
  b. It is taught to differentiate between skin lesions that are benign (non-cancerous) and malignant (cancerous) based on the selected variables from the training dataset.
  c. Precision, the classification report, and the confusion matrix are used to evaluate the model's performance. With the use of these tools, we can determine if the model is making any errors and how effectively it recognizes various kinds of skin lesions. They enhance the model's output and demonstrate how accurate the forecasts are.
- Random Forest:
  a. The chosen features are used to train a Random Forest model.
  b. It creates an ensemble of 100 decision trees, each of which gains knowledge from distinct data points.
  c. The majority vote determines whether the tumor is benign or cancerous, with each tree casting a vote.
  d. By averaging the output from all trees, it minimizes overfitting, manages noisy data well, and performs well with high-dimensional data, such as 300 features.

- Convolutional Neural Network (CNN):
  a. In order to automatically learn properties such as edges, forms, and textures from the skin photos, EfficientNetB3 is utilized as a CNN model.
  b. To categorize lesions as benign or malignant, the model incorporates additional thick (completely linked) layers and concludes with a softmax layer.
  c. EfficientNetB3 is utilized as a frozen model (unaltered) at first.
  d. To increase accuracy and generalization, the final 30 layers are subsequently unfrozen and retrained (fine-tuned) on the dataset.

4. Experimentation and Model Evaluation

4.1. Depiction Results

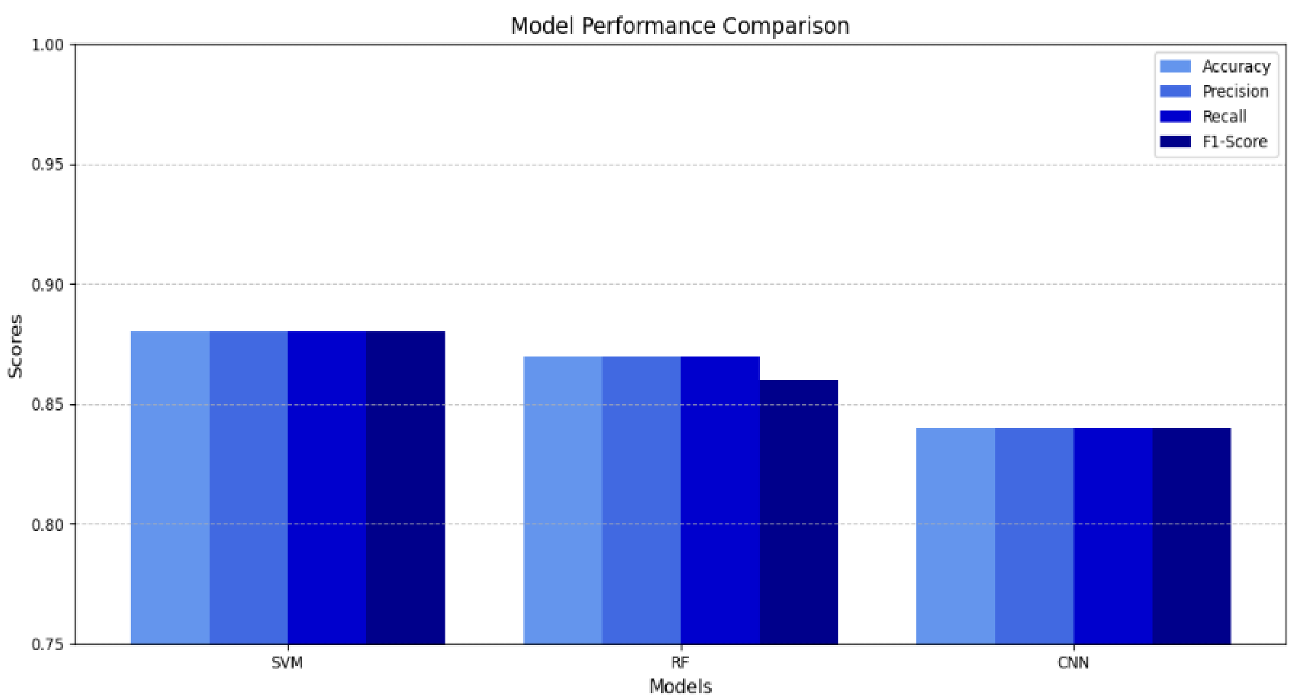
This study used the "Skin Cancer: Malignant vs. Benign" dataset to test three models: CNN, Random Forest, and SVM. Then we apply soft voting ensemble learning. Common evaluation criteria including as accuracy, precision, recall, and F1-score were used to assess each model's performance in classifying photos of skin cancer.

4.2. Validation/System Performance Evaluation

Model	Accuracy	F1-Score	Precision	Recall
SVM	**87.88**	**0.88**	**0.88**	**0.88**
RF	86.52	0.87	0.87	0.87
CNN	84.09	0.84	0.84	0.84
Ensemble Learning	95.91	0.96	0.96	0.96

[Table 1: Accuracy table of model]

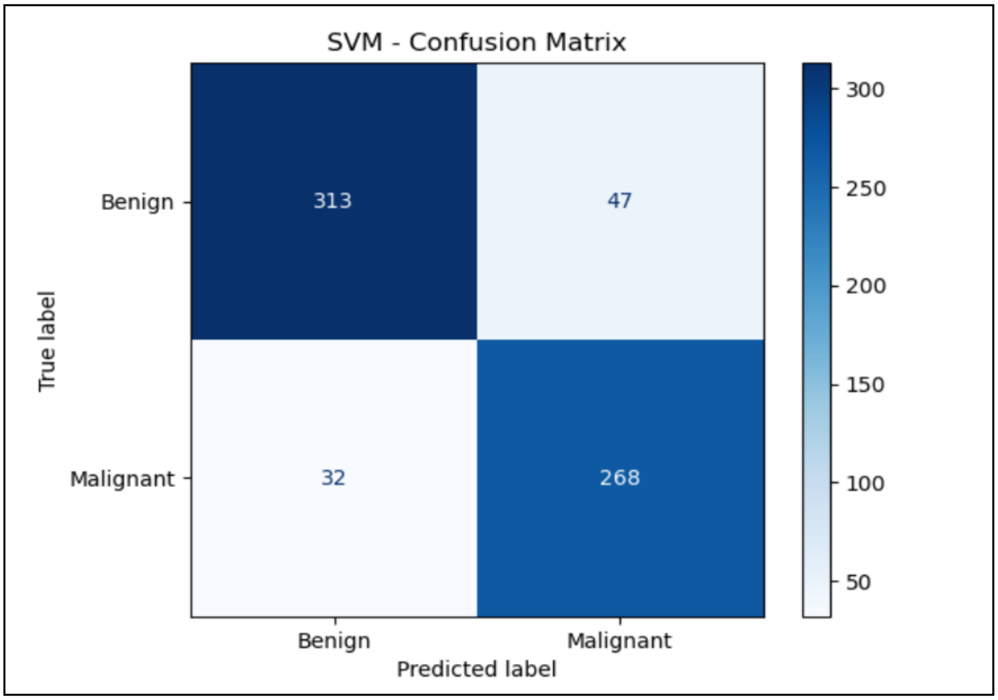
The SVM, RF, CNN model trained on the single dataset performs better than all other settings, as can be seen from the table. On the combined dataset, both models exhibit decreased accuracy; however, SVM, RF, CNN retains greater stability and generalization. Among all the model SVM gives highest accuracy of 87.88%. After applying Ensemble learning it gives 95.91% accuracy.



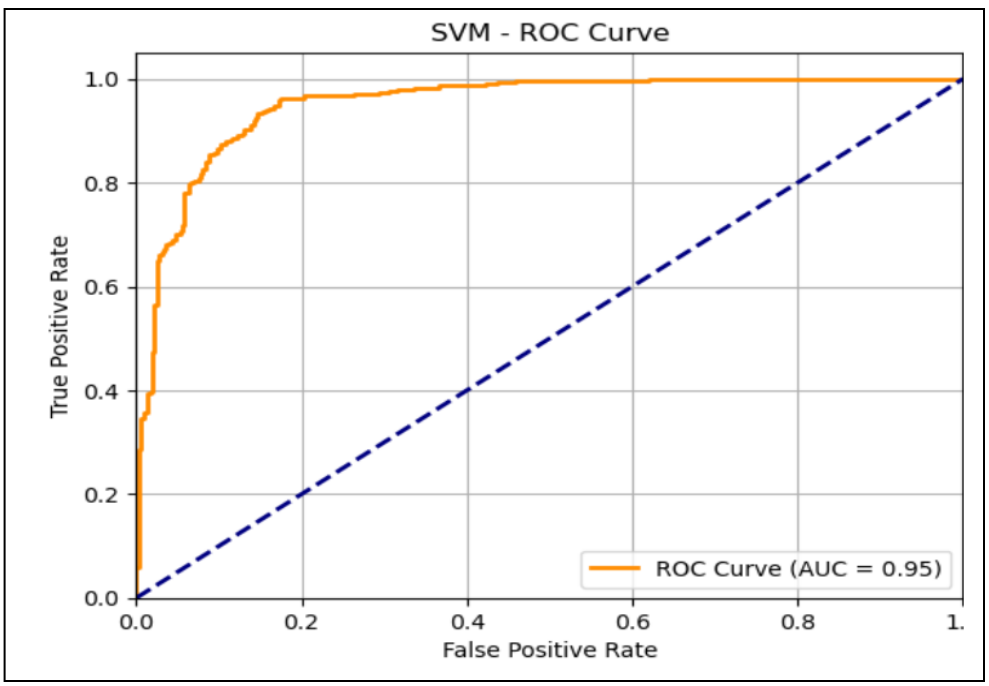
[Fig2: Compare the three Model]

The models' performance was assessed using training-validation curves and confusion matrices. These tools aided in determining whether the models were learning correctly during the training and validation stages and how well they classified the data.

- SVM
  i. Confusion matrix showed strong true positive and true negative rates.
  ii. The models capacity to differentiate between benign and malignant skin lesions was assessed using the ROC and AUC curves.

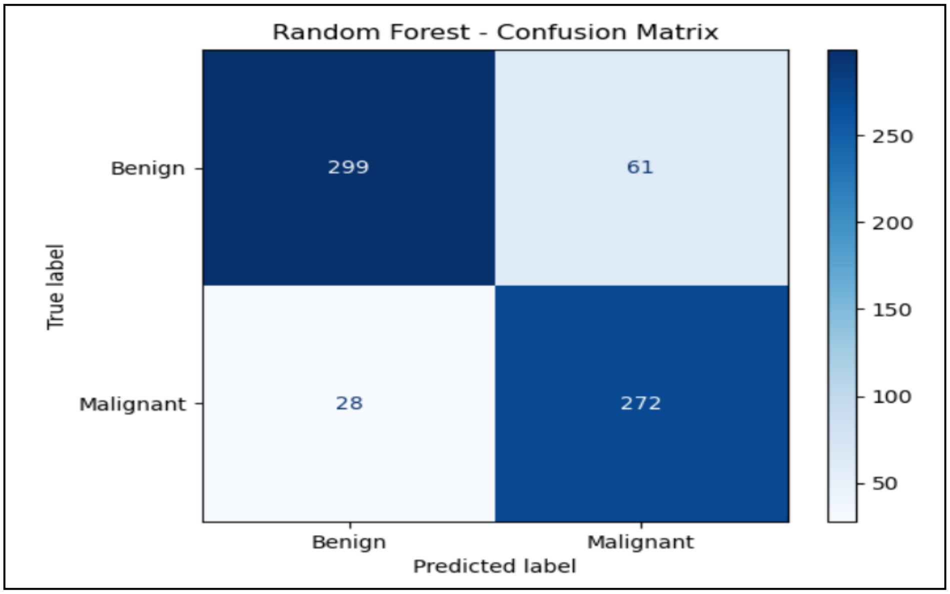


[Fig3: Confusion matrix of SVM]

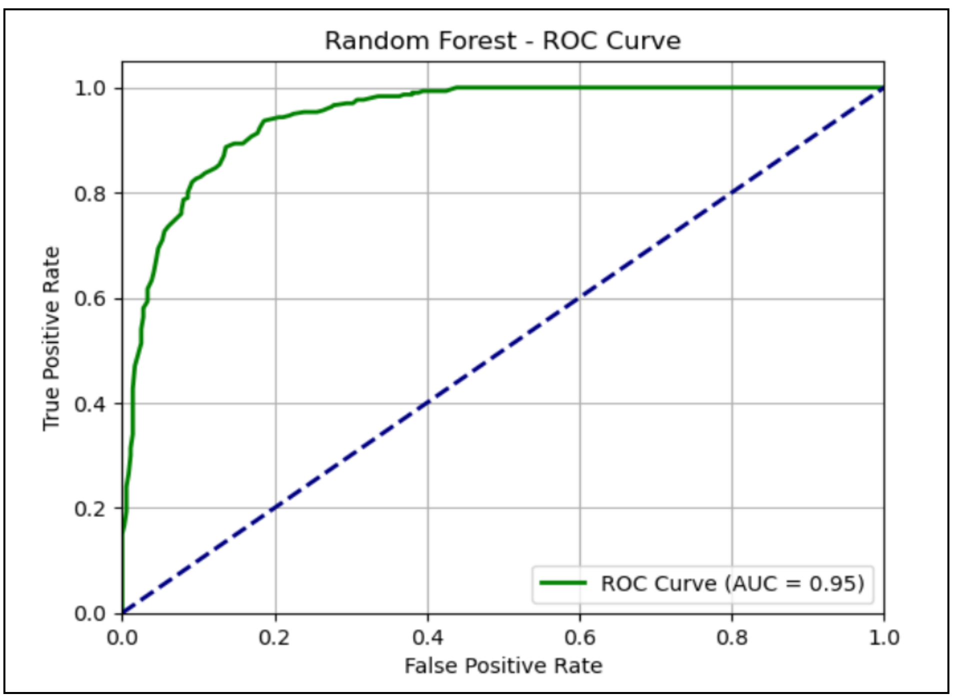


[Fig4: ROC curve of SVM Model]

- Random Forest
  i. The Random Forest model demonstrated outstanding classification ability with a high AUC of 0.95, as indicated by the ROC curve.
  ii. Random Forest's confusion matrix demonstrates that, although there were some false positives and false negatives, the model accurately predicted the majority of benign and malignant cases.

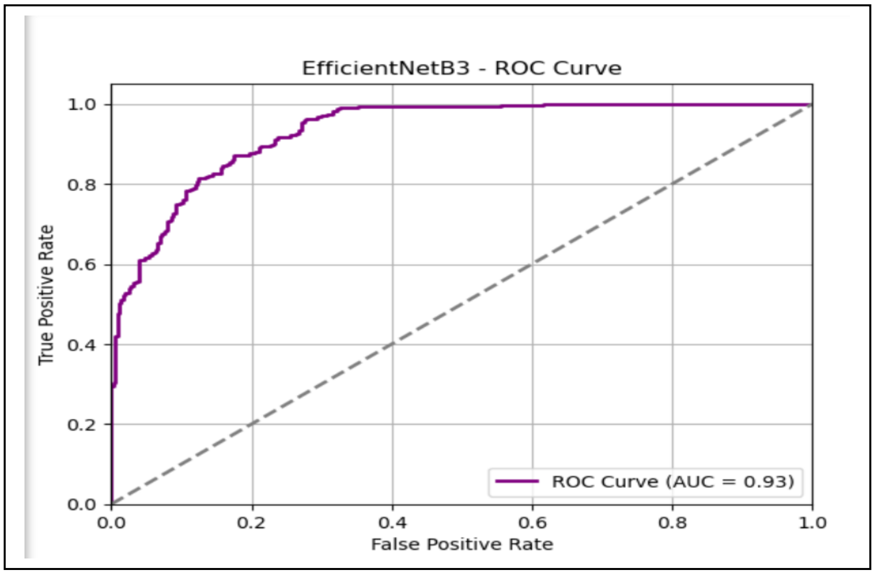


[Fig5: Confusion Matrix of Random Forest]

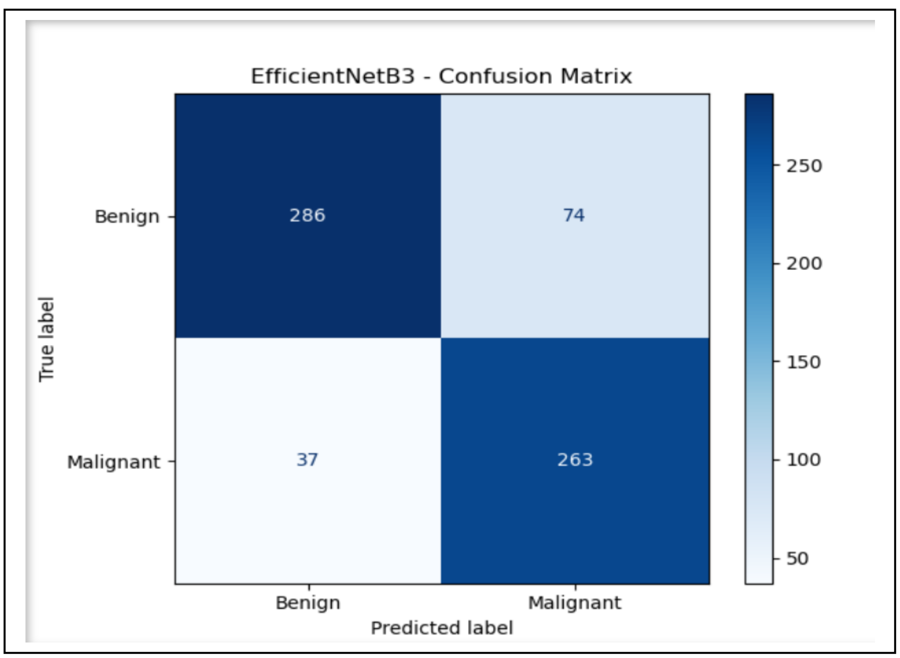


[Fig6: ROC Curve of Random Forest]

- CNN
  i. ROC Curve: EfficientNetB3's ROC curve indicates good model performance with an AUC score of.0 93, demonstrating a great classificat-ion ability.
  ii. Confusion Matrix: With a small number of false positives and false negatives, the confusion matrix shows that EfficientNetB3 successfully categorized the majority of benign and malignant instances.

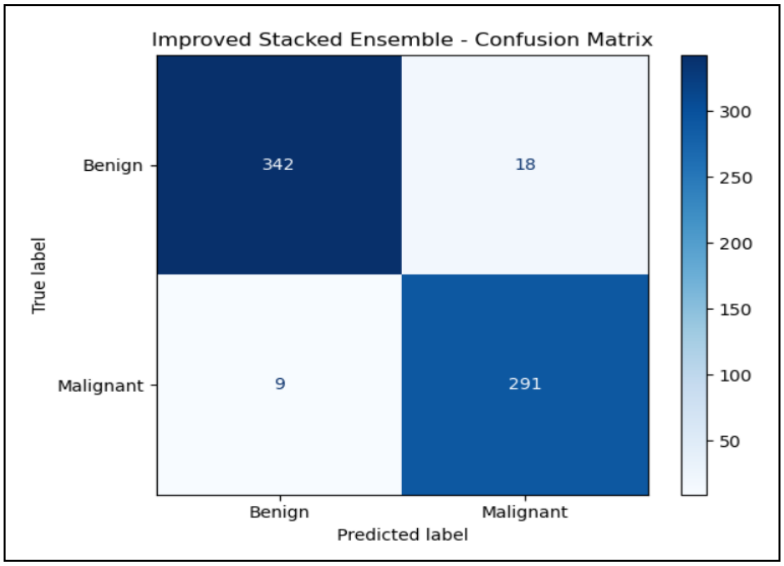


[Fig7: ROC and AUC Curve of CNN Model]

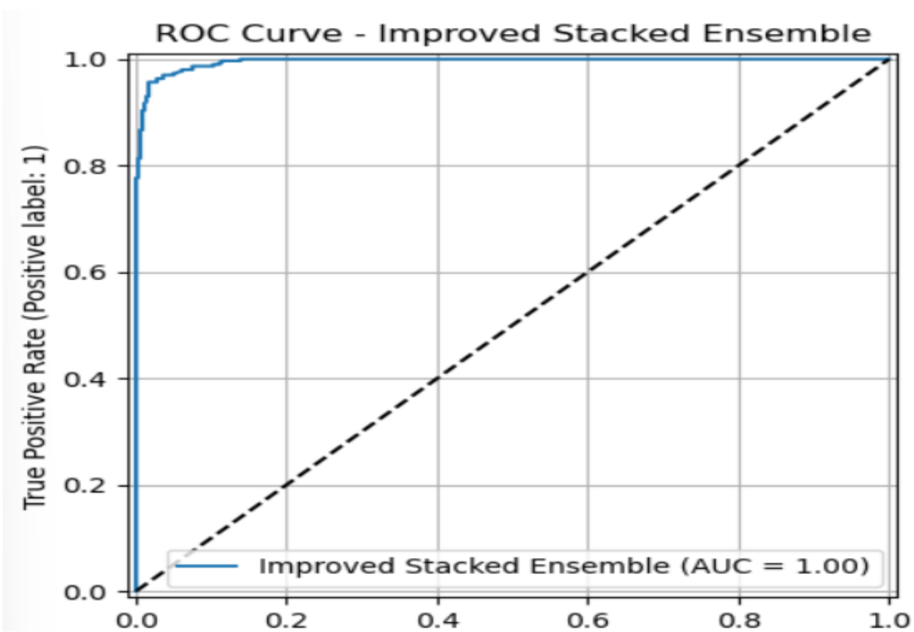


[Fig8:Confusion Matrix of CNN Model]

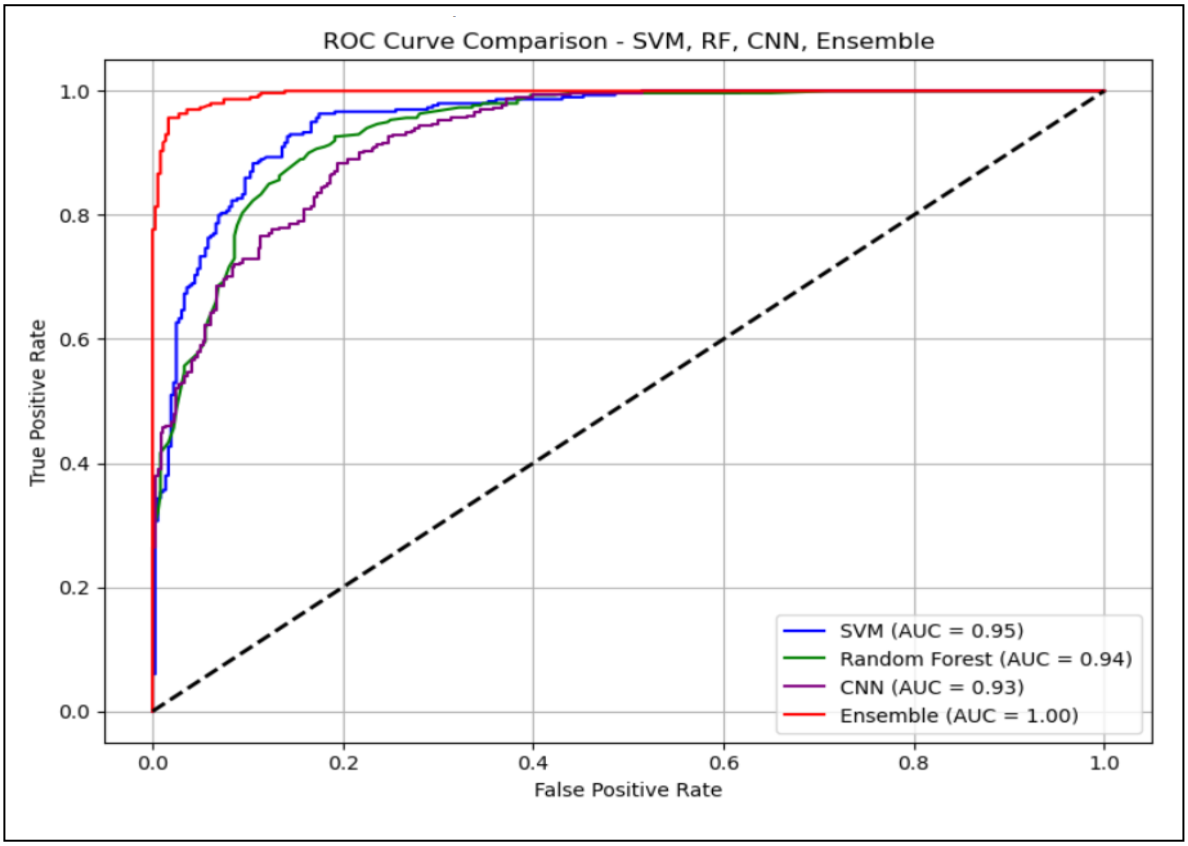
- Ensemble Learning:
    i. The ROC curve: AUC: 0.9955. Excellent model performance and class separability are indicated.
    ii. The matrix of confusion: False negatives and false positives are rare. high detection accuracy for both malignant and normal cases. shows a high level of efficacy and dependability.



[Fig8: Confusion Matrix of Ensemble Learning Model]



[Fig9: ROC Curve of Ensemble Learning]



[Fig11: ROC curve of SVM, CNN, RF, Ensemble Learning]

4.3. Discussions on Contributions

- Hybrid Extraction of Features:
  To improve classification, EfficientNetB3 and ResNet50 were used to extract rich, varied characteristics from lesion images.
- Selecting Features Effectively:
  Performance was increased and complexity was decreased by using SelectKBest with Mutual Information to select the best features.
- Sturdy Ensemble Model:
  Gradient boosting was used to combine CNN, Random Forest, and SVM predictions for increased accuracy and dependability.
- Thorough Assessment:
  For comprehensive performance insight, the evaluation was conducted utilizing the following metrics: accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix.
- Complete Automation:
  constructed a whole pipeline that can help with clinical skin cancer diagnosis, from input to prediction.

5. Conclusion and Future Scope

5.1. Conclusion

Melanoma is among the most common forms of cancer worldwide, which is the most deadly kind because of its high propensity to spread. Traditionally, dermatologists use eye examinations to make diagnoses, which are then confirmed by biopsies. Early skin cancer screenings are sometimes unavailable in underdeveloped or isolated places. However, new approaches to early and precise skin cancer detection are provided by machine learning (ML), a subset of artificial intelligence (AI). Convolutional neural networks (CNNs), a type of deep learning technique, can analyze skin scans and determine if a certain location is harmful or not. Thousands of annotated photos are used to train these models.

In several studies, by identifying minute variations in the photos, machine learning methods have equaled or even surpassed skilled medical professionals in identifying certain forms of skin cancer, such as melanoma. Furthermore, in situations where access to skilled dermatologists is limited or remote, machine learning (ML) can provide high-quality diagnostic assistance. This reach can be further expanded by ML-powered mobile applications and portable diagnostic equipment, which encourage early identification and treatment. Predictions may be off if models trained on biased or non-representative datasets are unable to generalize across various populations, skin tones, or lesion types. In addition, it is necessary to address ethical and regulatory issues like clinical accountability, informed consent, and data protection. Data scientists, dermatologists, and healthcare organizations must work together to overcome these obstacles.

Ensemble approaches, which combine the advantages of individual models to provide predictions with greater accuracy and robustness, were used to further improve performance. This method increases the system's overall reliability while reducing the shortcomings of individual models. All things considered, it represents a promising development in the use of machine learning in the healthcare industry.

5.2. Future Scope

- In order to increase patient survival rates and lower treatment costs, the initiative intends to use cutting-edge machine learning algorithms to detect skin cancer early.
- For feature extraction, two potent pre-trained convolutional neural networks—ResNet50 and EfficientNetB3—are employed. This enhances the depiction of skin lesion photos by capturing both abstract and fine-grained visual patterns.
- To determine which attributes are most pertinent, SelectKBest with Mutual Information scoring is used. This increases classification performance, decreases overfitting, and makes the model easier to understand.
- To enable comparison, three classifiers—Support Vector Machine (SVM), Random Forest, and a Convolutional Neural Network (CNN)—are trained separately to categorize images as benign or cancerous.
- The outputs from all three models are blended using a soft voting ensemble that considers the probability outputs from each model in order to increase robustness and overall prediction accuracy.

- We may assess the model's performance using metrics like as accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix. The model's advantages and disadvantages are clearly depicted by these instruments. They demonstrate the model's predictive accuracy, error rate, and overall performance balance. This aids in system improvement for better and more consistent outcomes.
- The system can process new skin lesion photos in real-time, which makes it appropriate for telemedicine and clinical settings where prompt and precise decision-making is crucial.

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