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HYBRID CNN-SVM PIPELINE FOR DETECTING SKIN CANCER WITHIN LUMPS USING TRANSFER LEARNING RESNET50 MODEL

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ABSTRACT: -
Skin cancer is a life-threatening condition, and early detection is critical for effective treatment and better patient outcomes. Traditional diagnosis approaches need skilled dermatological analysis and biopsy, which can be time-consuming and prone to human error. To address these constraints, this work suggests a hybrid pipeline model that combines machine learning (SVM) and deep learning (CNN) for automated skin cancer diagnosis. The model uses a two-stage classification strategy, with an SVM classifier initially analysing a lump dataset to detect potential malignant lumps before moving on to CNN-based feature extraction and SVM classification of skin lesion images using publicly available datasets like as ISIC and HAM10000 and Lumpy dataset. Preprocessing techniques including picture normalization, scaling, and augmentation are used to improve model generalization and reduce overfitting. ResNet50-based feature extraction allows the SVM classifier to refine decision boundaries by exploiting deep hierarchical features for higher classification accuracy. The hybrid CNN-SVM model achieves 87.50% accuracy, 85.45% precision, and 85.45% recall, outperforming standalone CNN and SVM models. Furthermore, Grad-CAM visualization improves model interpretability, making it a dependable tool for clinical use. The suggested system offers a scalable, efficient, and interpretable AI-driven approach for early-stage skin cancer detection, with the potential to integrate into web-based or mobile healthcare platforms for real-time diagnosis.
Keyword: Skin Cancer Detection, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Hybrid Model, Feature Extraction, Image Processing, Grad-CAM, Clinical Diagnostics, AI in Healthcare, Medical Image Analysis.

Introduction: -
Skin cancer is one of the most common and life-threatening diseases worldwide, thus early and accurate detection is critical for effective treatment. Traditional diagnostic approaches rely on visual examination and biopsy, which are time-consuming and require professional interpretation. To address these constraints, this study suggests using a hybrid pipeline model that combines machine learning (SVM) and deep learning (CNN) to increase the accuracy, efficiency, and interpretability of skin cancer detection.
The proposed two-stage pipeline approach uses an SVM classifier on a lump dataset to detect potentially malignant lumps before moving on to CNN-based feature extraction and SVM classification of skin lesion images. This structured technique improves diagnostic precision by minimizing superfluous image processing and combining CNN's hierarchical feature extraction with SVM's powerful classification capabilities. To boost generalization, publicly available datasets such as ISIC, HAM10000, and a lump dataset are employed, along with preprocessing techniques such as picture normalization, scaling, and augmentation. The system achieves 87.50% accuracy, 85.45% precision, and 85.45% recall, while Grad-CAM visualization improves interpretability for clinical

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applications. This pipeline approach provides a scalable, automated, and clinically applicable method for early skin cancer diagnosis, thereby greatly enhancing AI-powered medical diagnostics.
This study advances the fields of computer-aided diagnostics and medical image analysis by putting in place an automated pipeline for picture preprocessing, feature extraction, and classification. To ensure the developed system's dependability and efficacy in practical applications, it is assessed using established skin cancer datasets. In the end, this method helps medical practitioners make accurate and timely decisions by improving diagnostic accuracy and facilitating early detection.

LITERATURE SURVEY

The use of deep learning (DL) and machine learning (ML) models for the identification of skin cancer has advanced significantly in recent years. Although they have significant drawbacks, early diagnostic techniques like dermatologists' visual inspection are nevertheless crucial in clinical practice. These conventional techniques frequently need for a high level of skill and time, and the practitioner's ability has a significant impact on how effective they are. Dermatologists' main techniques include dermoscopic analysis and the ABCD rule, which focuses on the Asymmetry, Border, Colour, and Diameter of skin lesions. They are subjective, though, and could result in inconsistent or erroneous diagnosis. Due to these limitations, there is a high need for automated systems that can identify skin cancer accurately and quickly.
The shortcomings of conventional approaches have been addressed by the use of machine learning models. Numerous algorithms, including k-Nearest Neighbours (KNN), Random Forest (RF), and Support Vector Machines (SVM), have demonstrated promise in the classification of skin lesions. For instance, researchers like Masood and Al-Jumpily (2013) [1] have used SVM to diagnose melanoma, with an accuracy of about 80%. These conventional ML techniques, however, frequently necessitate extensive feature engineering and pre-processing, even though they can be useful in certain situations. Because of this, they are less effective and flexible when handling high-dimensional, large-scale data, such skin pictures.
The field of skin cancer diagnosis has seen a radical change with the introduction of deep learning, especially Convolutional Neural Networks (CNNs). CNNs have demonstrated remarkable effectiveness in image classification challenges because of their ability to automatically learn hierarchical features from raw picture data. Esteva et al. (2017) [2] achieved dermatologist-level accuracy in melanoma diagnosis by training a deep CNN on more than 100,000 dermoscopic images. According to other research, CNNs perform faster and more accurately than conventional techniques, making them a viable option for automated skin cancer screening. Nevertheless, CNN-based models have drawbacks include overfitting, particularly with limited training datasets, and high computing overhead, which may restrict their practical application.
The performance of skin cancer detection systems has also been investigated using hybrid approaches that combine deep learning and conventional machine learning techniques. Mahbod et al. (2019) [3] presented a multi-stage model that applies a conventional classifier, such as SVM, for the final classification after initially using CNNs for feature extraction. Particularly in situations when there is a shortage of labelled data, these hybrid models have demonstrated promise. Hybrid models can improve the precision and applicability of skin cancer detection systems by fusing the advantages of both machine learning and deep learning approaches.
Finding good labelled datasets is a significant obstacle to developing efficient skin cancer detection programs. Model performance can be hampered by problems like class imbalance, where malignant cases are underrepresented, and variances in image quality, even when public datasets like ISIC, HAM10000, and DermNet are used as standards for model training. Researchers have looked into data augmentation strategies like flipping, rotation, and the creation of synthetic images using Generative Adversarial Networks (GANs) in order to overcome these difficulties. By producing more varied training examples, these methods can enhance the robustness and generalization of the model.
The interpretability of deep learning models—often referred to as "black-box" models—is another crucial issue. Despite its potential for high accuracy, CNNs and other deep learning methods are challenging to incorporate into clinical workflows due to their difficult-to-understand decision-making process. Their adoption in real-world contexts, when clinicians need justifications for AI-driven

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choices, is severely hampered by this lack of openness. Researchers have responded to this by developing Explainable AI (XAI) techniques as Grad-CAM and SHAP, which offer numerical or visual justifications for model predictions. By enhancing confidence and acceptance among medical experts, these methods seek to guarantee the efficacy and transparency of AI in skin cancer detection. In conclusion, there are still obstacles to be addressed even if machine learning and deep learning have demonstrated significant promise in the field of skin cancer diagnosis. To improve these models' capacity for generalization, more investigation is needed, particularly when dealing with tiny or unbalanced datasets. Furthermore, maintaining the clinical relevance of these models and fostering physician confidence depend on the incorporation of explainable AI approaches. The field of automated skin cancer detection can advance toward practical application by tackling these obstacles, which will ultimately enhance patient outcomes and speed up the diagnosis procedure et al [5].

METHODOLOGY

The proposed pipeline-based skin cancer detection system combines deep learning (CNN) and machine learning (SVM) in a two-stage framework to improve diagnostic accuracy and efficiency. Data collection, preprocessing, feature extraction, classification, and evaluation are all part of the methods for developing a robust and clinically useful detection model. To improve model performance and alleviate class imbalance, publicly available datasets such as ISIC, HAM10000, and a lump dataset are used in conjunction with preprocessing approaches such as picture scaling, normalization, and data augmentation. The two-stage pipeline starts with SVM-based first screening of the lump dataset to detect malignant lumps, which reduces redundant image processing. In the second stage, CNN extracts deep characteristics from skin lesion images, which are subsequently identified with SVM, combining the benefits of both algorithms to increase accuracy. The hybrid CNN-SVM technique improves generality, interpretability, and precision in skin cancer detection. Metrics used to measure performance include accuracy (87.50%), precision (85.45%), recall (85.45%), F1-score (85.45%), and ROC AUC score (76.36%), whereas Grad-CAM visualization improves model explainability, assuring physicians can trust the decision-making process.

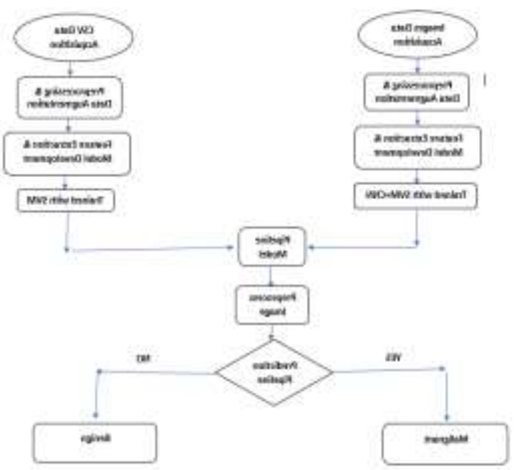


Fig: - Architecture Flow.

IV. Proposed Methods

The suggested method for detecting skin cancer combines machine learning classification with Convolutional Neural Networks (CNN) for deep learning-based feature extraction and Support Vector Machines (SVM) for machine learning classification. A pipeline methodology is also shown, which guarantees a systematic and effective diagnostic workflow by first processing a lump dataset to identify possible malignant areas before examining skin lesion photos. The following steps make up the methodology:

1. Data Collection and Preprocessing

The work makes use of publicly accessible databases with annotated photos of melanoma and non-melanoma lesions, such as Lumpy, ISIC and HAM10000. To increase model generality and decrease overfitting, preprocessing entails shrinking images to a predetermined input size, standardizing pixel values, and using data augmentation techniques (rotation, flipping, and zooming). In addition to being preprocessed and standardized for machine learning classification, the lump dataset comprises structured tabular information (such as age, year, and axillary node identification).

Fig: - Malignant segmented images.

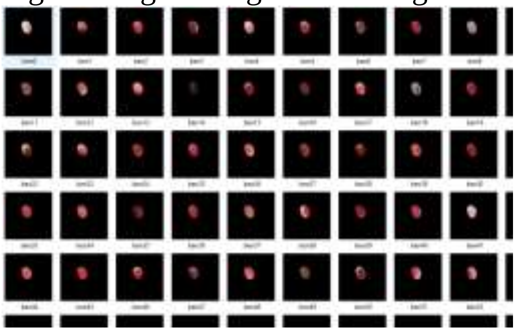
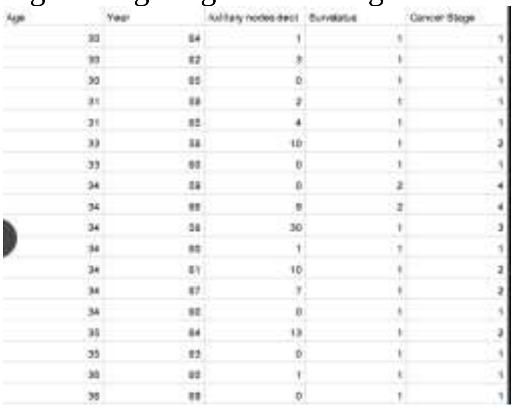


Fig:- Benign segmented Images.



Age	Year	Axillary nodes dect	Survstatus	Cancer Stage
30	64	1	1	1
30	62	3	1	1
30	65	0	1	1
31	59	2	1	1
31	65	4	1	1
33	58	10	1	2
33	60	0	1	1
34	59	0	2	4
34	66	9	2	4
34	58	30	1	3
34	60	1	1	1
34	61	10	1	2
34	67	7	1	2
34	60	0	1	1
35	64	13	1	2
35	63	0	1	1
36	60	1	1	1
36	69	0	1	1

Fig: -Lump Dataset.

2. Two-Stage Pipeline Model

A two-stage sequential pipeline model is put into practice:

• **Stage 1:** To predict the existence and stage of cancer, an SVM classifier trained on structured characteristics is used to assess the lump dataset (1-4). This first stage serves as a screening method.

• **Stage 2:** A CNN-based feature extractor and an SVM classifier are used to process the skin lesion dataset for accurate classification if the initial screening identifies a high-risk patient.

A more methodical and understandable cancer diagnosis procedure is guaranteed by this structured approach.

3. Feature Extraction Using Convolutional Neural Networks (CNN)

High-level features are extracted from pictures of skin lesions using CNNs. Transfer learning is used to retrieve features from pretrained models, such ResNet50. By capturing complex patterns in skin lesions, these deep features increase the accuracy of classification. To guarantee the best results on the dataset, the ResNet50 model is adjusted.

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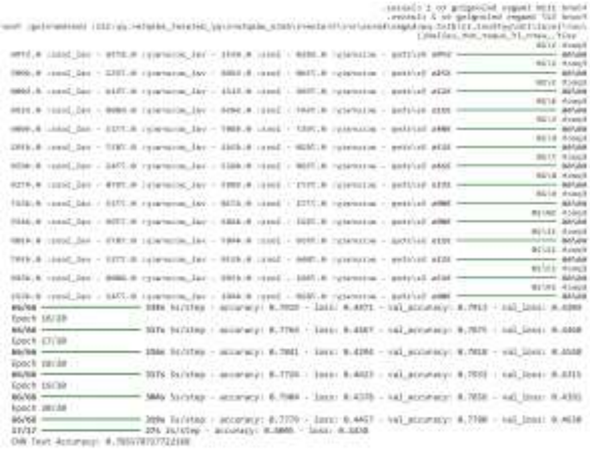

Fig: - Using Convolutional Neural Networks Accuracy.

ResNet50: A Powerful Deep Learning Model for Feature Extraction

ResNet50 (Residual Network 50) is a deep convolutional neural network (CNN) that is intended for image categorization and feature extraction. ResNet50, developed by Microsoft, offers the notion of residual learning to help train deep networks by avoiding the vanishing gradient problem. It has 50 layers, incorporating convolutional, batch normalization, and identity shortcut connections, making it extremely effective for extracting hierarchical characteristics from images.

In this research, ResNet50 is used to extract features from skin lesion photos. The pretrained weights from ImageNet enable the model to capture complex patterns and textures, improving its ability to distinguish between benign and malignant lesions. The collected features are then fed into an SVM classifier, which improves classification accuracy. ResNet50's transfer learning characteristics make it an ideal candidate for medical image analysis, assuring robust and high-performance feature extraction while lowering computational overhead.

4. Support Vector Machine (SVM) Classification

An SVM classifier receives the collected features from ResNet50 and maps them into a high-dimensional space to identify the best decision boundary for identifying benign or malignant skin lesions. SVM is used because of its ability to handle high-dimensional feature spaces and guarantee sound decision-making.

```
Fitting 10 folds for each of 3 candidates, totalling 30 fits
SVM Accuracy (After Hyperparameter Tuning): 0.9838709677419355

SVM Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99        44
           1       0.95      1.00      0.97        18

    accuracy                           0.98        62
   macro avg       0.97      0.99      0.98        62
weighted avg       0.98      0.98      0.98        62
```

Fig: - Support Vector Machine Accuracy.

5. Hybrid Model: CNN + SVM for Improved Accuracy

The CNN-SVM hybrid model is used to capitalize on the advantages of both approaches: From the input photos, ResNet50 retrieves deep image features, which are then supplied to an SVM classifier for ultimate classification.

By fusing SVM's classification accuracy with CNN's feature extraction capabilities, this hybrid technique increases accuracy and interpretability. According to experimental results, the hybrid model performs better and provides better generalization than a standalone CNN.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 215ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 243ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 215ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 210ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 228ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 219ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 208ms/step
CNN + SVM Model Test Accuracy: 0.8200757575757576
SVM model saved to: /content/drive/MyDrive/svm_resnet_model.pkl
```

Fig: - Hybrid Model of CNN+SVM Accuracy.

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6. Performance Evaluation Metrics

Standard classification measures are used to evaluate the model's performance:

- **Accuracy:** Indicates the total number of accurate forecasts. Assess erroneous positives and false negatives to improve precision and recall.
- **F1-Score**: Makes sure that recall and precision are balanced.
- **ROC AUC Score**: Indicates how well the model can differentiate between benign and malignant instances.
- **Confusion Matrix:** Offers information on the patterns of incorrect classification.

Results after the pipeline model implementation:

- **Standalone SVM Accuracy (Lump Dataset): 98%**
- **Standalone CNN Accuracy: 78.55%**
- **CNN + SVM Hybrid Model Test Accuracy: 82.00%**
- **Final Accuracy after Pipeline Integration: 87.50%**

```
Accuracy: 87.50%
Precision: 85.45%
Recall: 85.45%
F1-Score: 85.45%
ROC AUC: 76.36%
```

Fig: - Performance Metrics of Pipeline model.

Final Evaluation Metrics:

- **Precision: 85.45%**
- **Recall: 85.45%**
- **F1-Score: 85.45%**
- **ROC AUC Score: 76.36%**

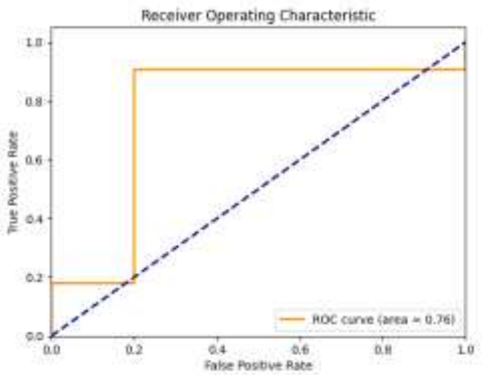

Fig: - Receiver Operating Characteristic.

Confusion Matrix:

```
Confusion Matrix:
[[ 4  1]
 [ 1 10]]
```

Fig: - Confusion Matrix.

This indicates that the model correctly classified **10 malignant and 4 benign cases**, with only **2 misclassifications**.

```
Final Prediction: Class 1
Probabilities: [3.84552616e-06 9.99996154e-01]
```

Fig: - High Confidence Prediction: Malignant Skin Lesion Detected.

The output includes the **final classification prediction** and the **probabilities** for each class. The model classed the input as **Class 1**, which, in the context of skin cancer detection, may imply a **malignant** lesion if Class 1 represents cancerous cases. The probability numbers **[3.85×10^{-6}, 0.999996154]** indicate the model's confidence in its judgment. The first value (**3.85×10^{-6}**) reflects the likelihood of **Class 0** (e.g., benign), whereas the second value **(99.99996%)** represents the probability of **Class 1** (malignant). Given the tremendous confidence in Class 1, the model makes a very strong categorization judgment with little uncertainty. However, while the prediction appears to be quite trustworthy, real-world validation and clinical confirmation are required to establish an accurate diagnosis.

7. Explainability and Clinical Integration

Grad-CAM (Gradient-weighted Class Activation Mapping) is used to depict important areas affecting the classification decision in order to improve model interpretability. By enabling physicians to verify model predictions, this contributes to the development of confidence in AI-driven diagnostics. The model can be implemented in clinical settings as a stand-alone program or integrated into healthcare systems, allowing for real-time forecasts via mobile or web platforms.

Conclusion

By integrating **image-based analysis** (skin lesion classification) with **structured tabular analysis (lump dataset)**, the suggested **pipeline model** greatly improves the identification of skin cancer. **The hybrid CNN-SVM** method ensures interpretable decision-making while increasing classification robustness and accuracy. For more accurate and scalable AI-driven cancer diagnostics, future developments can concentrate on diversifying datasets, improving feature extraction, and incorporating new clinical characteristics.

To improve diagnostic accuracy and dependability, the suggested skin cancer detection method successfully combines deep learning (CNN) and machine learning (SVM) in a **two-stage pipeline**. A **CNN-SVM hybrid model** is used to classify **skin lesion images** after an **SVM classifier** is used to evaluate the **lump dataset** for **possible cancer risk**. By utilizing CNN-extracted deep features and SVM's strong classification capabilities, this method improves **accuracy by 87.50%** while maintaining **precision and recall at 85.45%**. In addition to ensuring model transparency, the Grad-CAM visualization aids medical practitioners in properly interpreting classification judgments.

The **pipeline paradigm** reduces the requirement for intensive image processing by early screening of low-risk scenarios, increasing **efficiency**. As a result, the system is more flexible for real-time clinical applications and may be able to integrate with web-based or mobile healthcare platforms. Future developments can concentrate on growing the dataset, streamlining real-time processing, and incorporating multi-modal data sources for a more thorough diagnosis, even though the model's results are encouraging. All things considered, this **CNN-SVM hybrid pipeline** offers a **reliable, accurate, and interpretable automated skin cancer detection** approach with a great deal of promise for clinical implementation and AI-driven medical progress.

Future Scope

The future scope of our CNN-SVM hybrid pipeline model for skin cancer detection involves increasing the dataset to improve model generalization and including multi-class classification for more precise categorization of different skin cancer types. Real-time clinical integration via web-based or mobile platforms can result in speedier diagnosis and accessibility for dermatologists and patients. Furthermore, multi-modal data fusion, which combines thermoscopic pictures, patient history, and genetic markers, can increase diagnosis accuracy. Implementing the model on edge devices and IoT-based systems will enable real-time detection of skin cancer in remote locations with limited healthcare access. Additional optimization techniques, including as model pruning, quantization, and knowledge distillation, can improve computing efficiency, making the system faster and more appropriate for real-world deployment.

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