**International Journal of Engineering & Extended Technologies Research (IJEETR)**

**|ISSN: 2322-0163|** www.ijeetr.com **| A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |**

**| Volume 8, Issue 2, March - April 2026 |**

**DOI:10.15662/IJEETR.2026.0802245**

# Skin Disease Classification using Deep Learning with Grad-CAM Visualization

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**Publication History:** Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

**ABSTRACT:** Skin cancer is one of the most widespread and terminal skin diseases all over the world. Prompt diagnosis is quite vital in improving the survival rates of patients through proper diagnosis. The new trends in DL have enabled the automatic analysis of skin lesions through the use of classification and object recognition. To have a complete examination of the skin diseases, this writing presents a two-branch DL architecture by integrating image-level classification and localization of abnormality regions. A set of a transfer-learning architecture, including VGG16, ResNet50, InceptionV3, DenseNet121, Xception, ConvNeXt-Tiny, and an ensemble are trained on labeled dermoscopic images to classify the images into groups. YOLO based models such as YOLOv5s6, YOLOv8, YOLOv9 and YOLOv11 are trained with notes of the YOLO formatted bounding boxes. It has been extensively experimented and ConvNeXt-Tiny is the most successful at classification (94.88% accuracy), and YOLOv8 is the most successful at recognition (73.9% mAP, 72.2% precision, and 79.6% recall). The explainable AI techniques based on gradient-based camera (Grad-CAM) are applied to visualize the significant regions influencing predictions and simplify the model. Moreover, an application based on Flask web application is being developed to enable real-time inference, which is a merger of detection, classification, and visual description to assist health care specialists in making decisions.

**KEYWORDS:** Skin cancer detection, deep learning classification, YOLO-based object detection, ConvNeXt-Tiny, explainable AI, Grad-CAM, ensemble learning, Flask web application”

## I. INTRODUCTION

Some of the most prevalent health issues in the world are skin cancer and other skin related disorders. The cases are gradually increasing due to factors such as prolonged exposure to UV, pollution and lifestyle transformations [1]. The timely and correct diagnosis of skin issues is highly valued in reducing the intensity of illnesses and increasing the mortality rate of patients. Yet, the fact that the appearances of various skin conditions are similar may make the diagnosis difficult, even in experienced doctors, leading to the delay of estimates or even incorrect ones [2]. This hardship of this issue reveals the sensitivity of the technology doctors require to assist them in diagnosis.

New advancements in computer vision and AI have created the opportunity of solving skin diseases with the help of digital pictures automatically [3]. Deep-learning-based image analysis systems are able to acquire rich visual appearances such as color distribution, texture patterns and lesion edges that are highly significant to determine the difference between benign and cancerous skin conditions [4]. Such mechanisms render a subjective decision and the application of the same judgment in most of the cases to be less significant as people are concerned [5]. An increasing array of dermoscopic and clinical skin images are becoming accessible and this has accelerated research in this field even further.

The ML and DL have presented a considerable potential in solving the problems that have several classes of skin diseases [6]. Such approaches are able to process vast volumes of image data in a short period and adapt to variations in the appearance of lesions among individuals and other imaging circumstances [7]. The automated analysis is not only useful in assisting doctors to make decisions, but it also enables large-scale screening, which is particularly useful in areas where access to specialized medical services are scarce [8]. The reason is that intelligent diagnostic tools are now becoming a significant component of contemporary healthcare infrastructure.

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802245

The integration of image-based diagnostic tools with the web technologies has rendered them even easier to use and access [9]. Online applications allow users to post images of their skin at a distance and receive a reply immediately. This assists in conducting early screening and follow-up without necessarily having to make fast visits to clinics. Such systems are particularly useful in rural and underserved areas, which lack medical resources [10].

The overall aim of the work is to design an intelligent and user-friendly system to analyze skin diseases automatically to assist in early diagnosis, simplify the process of identifying skin conditions, and make the system more accessible via the web-based interface. With a combination of intelligent image analysis and convenient deployment functionalities, the system is anticipated to enhance clinical assist, reduce the amount of manual labor, and result in enhanced medical care delivery.

## II. RELATED WORK

Abdulredah et al. [11] demonstrated how to make skin cancer classification a less biased process with the help of deep feature fusion methods. They primarily worked on how to borrow beneficial characteristics of various DL models and extract them to make the outputs of classification more accurate and equitable. The experiment revealed that diagnostic reliability can be enhanced by a large variety of skin lesion types using fused representations to deal with class imbalance and feature diversity. Dorathi Jayaseeli et al. [12] proposed an intelligent framework that combines the Squeeze-Excitation DenseNet models with meta-heuristic-based ensemble learning models. The authors paid special attention to adaptive feature recalibration and optimization algorithms in order to make the discriminative power more efficient. Their fusion-based solution performed well with regards to capturing the global and the local lesion features. This simplified the process of categorizing complex series of skin cancer.

Likhon et al. developed a programme named SkinMultiNet [13]. It is a web-based DL-based system that predicts skin cancer. The project demonstrated the significance of having proper systems that do not only sort items appropriately but also simplify access to them by simple platforms. They demonstrated with their system how in the real world deep models may be applied to assist in remote diagnostics. A ML model that classifies skin diseases based on CNN was developed by Allugunti [14] in 2014. The research was largely regarding the acquisition of spatial and texture-based features of dermoscopic images. It illustrated that CNN-based networks have the capacity of distinguishing various kinds of skin illnesses with minimal manual labor.

Mandal et al. [15] investigated the possibility of combining active learning with particle swarm optimization to enhance the process of detecting skin cancer. They could select informative samples to be used in training thereby minimizing the effort that was required to label things and enhance the performance of the model. Learning speed and accuracy in classification increased when optimization techniques were used along with deep CNN models. Mavaddati [16] proposed an idea of mixed DL model, in which the long-term and short-term memory networks are used to classify skin cancers. The analysis was on the sequential and contextual association of the deep features extracted. This enabled the lesion patterns of complex lesions to be better modeled and the classification to be more stable.Suleiman et al. [17] applied transfer learning and RF algorithms to develop a hierarchical binary classification system with two steps. Their approach divided the task of sorting into hierarchically made decisions. This enabled the distinction of cancerous lesions and non-cancerous lesions to be easier and also reduced the factor of error in classification. Noaman et al. [18] did not just categorize lesions on the skin into two but applied transfer learning based on AlexNet to categorize lesions into over two clades. They found that even deep networks which have been trained may be fine-tuned to enable dermatologists make more precise diagnoses of a broad variety of skin issues.Kumar et al. [19] proposed an algorithm which consists of a binary tree growth algorithm, and extracts deep features. The research was largely based on the structured decision-making procedures which enable the things to be easily understood and yet at the same time as good as classify the things with the assistance of the deep representations. A combination of multi-resolution empirical mode decomposition and local binary pattern features was developed by Samsudin et al. [20], as a method of classifying skin lesions. Their work demonstrated the relevance of combining signal decomposition and texture analysis to obtain fine-grained features of lesions of the skin. This assists in the explanation of the distinction between various skin lesions.

## III. MATERIALS AND METHODS

It proposes a novel approach based on the idea of DL to autonomously search skin diseases. It integrates classification, lesion detection and explainability into one process. A number of transfer learning-based classification models are applied to dermoscopic images. These are VGG16, ResNet50, Inception V3, DenseNet121, Xception, ConvNeXt-Tiny and an ensemble model to make the models stable and more applicable in other cases. In order to precisely identify

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abnormal conditions, sophisticated object detection models such as YOLOv5s6, YOLOv8, YOLOv9 and YOLOv11 are utilized to detect and label skin lesions. Those models are developed on the basis of new DL-based diagnostic models [23]. To make the model less vague, heatmaps whose areas indicate the most crucial areas that influence predictions are formed with the help of Grad-CAM. This assists in clinical interpretability which is emphasized in past research [25]. The entire system operates by means of a web application created in Flask that allows users to log in, share pictures, make real-time inferences and view the outcomes. The approach is based on the concept of deep feature extraction applied in automated systems in the classification of skin diseases [21] and offers a simple to understand and utilize diagnostic support tool.

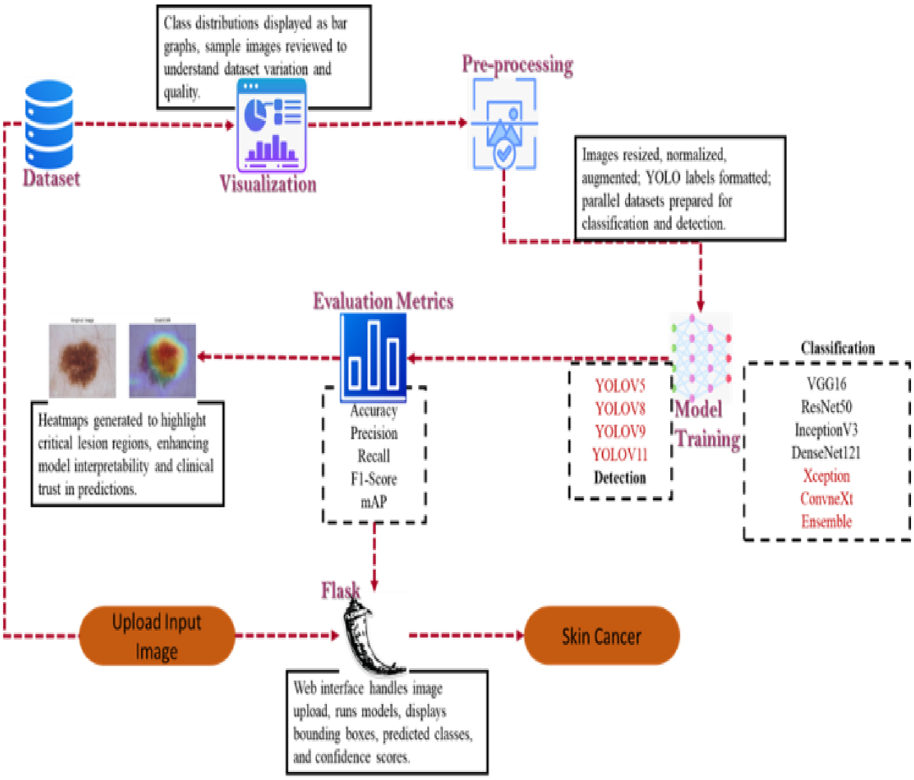


Fig.1 System Architecture

Figure 1 illustrates the installation of the proposed approach to create a complete ML pipeline to diagnosticate skin cancer. It begins by obtaining datasets and visualizing them in order to visualize the distribution of classes. Then, there are pre-processing activities such as shrinkage and addition to the datasets. In the process of training, it includes detection (YOLOv5 to YOLOv11) and classification (VGG16, ResNet50, etc.) architecture. The ratings of the performances are performed with the help of standard evaluation measures and Grad-CAM heatmaps that make them easier to comprehend. Finally, the system and real-time image analysis are configured with the help of a Flask web interface.

A) Dataset Collection:

The data presented to carry out this study consists of microscopic images of five skin samples of five groups, namely normal, arsenic, eczema, and psoriasis. In the task of classification, images with the corresponding labels of classes are gathered in a publicly available skin disease identification dataset, which means that a variety of skin conditions and visual features are represented. These images have been given a name to allow them to be utilized in the classification of multi-class skin diseases. In the detection job, individual data set is collected which contains images of skin lesions which are marked with YOLO text indicating the location where the images are abnormal. It can be marked with these marks in order to find the diseased spots precisely in the pictures. In order to develop and test models, the two datasets are 70:30 split into training and validation splits. This ensures that there is a balance in classes in different sections and that performance assessment is done precisely.

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B) Pre-Processing:
Pre-processing ensures that pictures of the skin are good and consistent in size, scale, and illumination before analysing them. It establishes pictures and notes in the right formats to make learning reliable towards finding things as well as classifying them.

Visualization – The characteristics of a dataset are known with the help of visualization to ensure that the data is correct prior to training a model. A bar graph to present class distribution makes it convenient to observe the number of pictures one can have of any type of skin disease, including arsenic, eczema, melanoma, normal, and psoriasis. This graphic will allow identifying the imbalances in classes and ensure that any groups are fairly represented. Examples of images in each category are labeled in order to have a more precise idea of visual patterns, such as alterations in texture and color, the boundaries of lesions, and other surface anomalies. To the detection dataset, sample images with bounding box labels are displayed to ensure that the afflicted regions are properly identified. These graphical checks are useful in ensuring that the annotations have been right and increase confidence that the data is fit to be utilized. All in all, visualization assists in the exploratory analysis, simplifies the dataset and ensures that the classification labels, as well as the detection annotations, correctly correspond to the images they are associated with.

Processing – With image processing, data must be made available on the individual basis, where it goes through detection and classification, but the data streams should not be terminated. The images are rescaled to a common input scale and made to fit the range of normal pixel values in order to stabilize learning. Such techniques as rotating, flipping, zooming, and changing the color of data help to make it more variable and better generalized. Under the classification branch, the processed images are matched with the names of the diseases associated with them. The detection branch connects images with YOLO text-based annotations which indicate the edges of the images. The detection process requires setting up paths of datasets and names of classes in a data.yaml file. Such a structured system ensures that it is compatible with YOLO models and it is feasible to load data easily. The system enables classification of diseases and identification of their location within a single workflow with high accuracy and precision by maintaining different datasets that are synchronized.

C) Algorithms:
VGG16 is a form of profoundly CNN with a basic and uniform structure composed of totally connected layers stacked one above the other with convolutional layers possessing tiny receptive fields. It acquires edges, textures, and complex patterns in pictures with time, extracts hierarchical bodies of visual data. The depth has 16 weight layers and enables learning of features in a stable manner without complicating the architecture. VGG 16 in the case of skin picture analysis is effective in identifying small visual details during analysis such as color, edges, and texture variations. Its pre-trained weights allow feature transfer to be achieved with ease, offering easier training and it is also able to do a good job of making a representation. Although it is more expensive and slower to execute, the model is able to extract features and is always competitive in medical picture classification.

ResNet50 Provided the additional learning to eliminate the issue of deep network breakdown with shortcut links. The network not only learns residual functions but also allows gradient flow across fifty layers, allowing the map to be learned. The design gives the ability to capture finer details without slowing the system. In order to identify low-level and high-level semantic patterns of skin diseases, ResNet50 retains information between levels because of context. The remaining blocks stabilize the training and increase the rate of convergence. It is able to make the distinction between slightly different skin conditions because it can model complex visual representations, particularly when the zoning of lesions and color distributions is very different between the categories.

InceptionV3 implemented convolutional processing of raw data using several scales of convolution by effectively executing the data through parallel convolutional paths with different kernel sizes. The technique allows simultaneous extraction of both fine and coarse features, and thus enhances the richness of the representation. Computations can be made faster and dimensionality reduction factorized without losing depth. InceptionV3 achieves good performance in medical image analysis by modeling the lesion form, size, and texture in an image by joining spatial features at various resolutions. The depth and width of the architecture are well balanced, and this enables good learning without unnecessary parameter expansion. Its systematic aspect of fusing of features assists in narrating the distinction between groups of skin illnesses that appear very similar.

DenseNet121 has dense connectivity, implying that a layer receives feature maps of all levels that preceded it. The design promotes the reuse of features and enhances the distribution of gradients across the network. The reason why denseNet121 is able to capture subtle trends in visual data with fewer parameters than the conventional deep networks

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is due to the fact that information is preserved at the layers. Small differences in texture and the borders of lesions can be detected more easily because the links are dense and placed in the corner of the skin images. The model accelerates the learning process and reduces redundant information. This is why it can be applied to the complex medical images in which distinguishing characteristics could be minimal or be similar across the classes.

Xception is a variation of the concept of Inception which applies depthwise separable convolutions rather than normal convolutions. This approach isolates learning characteristics by space and channels and this makes it more effective and potent. The design allows you to achieve a more detailed design on less effort on the computer. Xception performs well in identifying the complicated patterns in color, texture, and the tumor structure when analyzing skin diseases. Its shape facilitates the acquisition of visual cues which are specific to a particular class and at the same time enable high generalization. The model is effective in a case where it is required to have an exact distance between elements and an intense feature abstraction.

ConvNeXt- Another recent convolutional network is Tiny, which is designed on the principles of transformer design but remains as efficient as a convolutional network. It must learn features, and in that regard, it has larger kernel sizes, layer normalization and less complicated block layouts. The design enhances information in space and context among areas of images. ConvNeXt-Tiny is superb at discovering global and local visual patterns in skin image recognition, which enables the ability to distinguish between types of diseases with high accuracy. Its balanced structure compliments it with faster computations, and thus it is ideal with high-resolution medical images that require careful analysis of the surrounding.

An ensemble model combines the results of a number of independent classifiers and assembles them to create the overall decision with more dependability. The grouping of models reduces the bias and variance of individual models by using results of other architectures. The various elements of the visual data, such as shape, color or texture are captured in each of the participating models. In the case of skin diseases, ensemble learning renders it more difficult to have erroneous classifications by noise or images of low quality. The decision taken jointly indicates that all the models concurred on this and hence the final predictions become more reliable and people have more confidence about the predictions particularly in challenging instances where there is overlapping of the visual features.

YOLOv5s6 is a one stage object recognition model which is able to do both localization and classification simultaneously. During one forward step, it breaks images into grids and predicts bounding boxes and confidence scores. The s6 version has better input resolution resulting in easy locating small or irregular areas. When looking at skin lesions,Well discovers where it is not normal and retains rapid thinking. Its small size and light weight ease finding the things without the accuracy to space and thus, it can be applied in real time lesion localization tasks.

YOLOv8 adds enhancements to the architecture that would result in better recognition and more stable training. It improves the prediction heads and feature extraction and simplifies the model setup. The design helps to deal with complex backgrounds and objects that overlap easier. YOLOv8 is more efficient in space with regards to locating lesion areas in medical images. Its better loss operations and the enhanced training process ensure that the prediction of the bounding box remains correct and that the detection performance remains constant across a variety of skins image conditions.

YOLOv9 works on the improvement of flow of information and use of features through the advanced training methods and improved network design. It improves the representation learning in detecting hard tasks due to small visual differences. In the event of localization of skin abnormalities, tumor areas with low contrast or rough edges are picked by YOLOv9. The model emphasizes the idea that features ought to remain consistent across scale in order to be consistently determined in a large variety of image scenarios and to ensure that computations are as light as possible.
YOLOv11 refines the YOLO family, it is more advanced and has a higher feature fusion and prediction accuracy. It enhances multi-scale representation and spatial awareness that enables one to identify the position of complex areas. YOLOv11 is able to effectively detect different sizes and shapes of lesions in skin images because it will integrate the contextual information among the layers. The thoughtful design of it allows making the training stable and able to predict the regions with good accuracy that can be used to find the spots of skin that do not appear right with high reliability.

D) Integration of XAI & Flask:
Grad-CAM is applied to introduce explainable AI to the system to ensure that the model is more transparent and creates trust in the professional community. Grad-CAM generates heatmaps by highlighting image sections whose influence on

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the classification decisions is significant. These images aid in illustrating that the model is not concentrating on any random noise but rather in medically significant areas of lesion. It assists in making accurate predictions that are easy to interpret in case of research on skin diseases.,The acquired models are implemented in a basic, interactive web application based on the Flask framework. It involves user authentication, uploading images, conclusion drawing based on models and real time sending of results. Flask simplifies the process of communication between front and back end. It displays the results of classification, detection, confidence and visual description in a simple interface.

## IV. EXPERIMENTAL RESULTS

Accuracy: The ability of a test to distinguish between sick and healthy individuals is known as the accuracy of the test. In order to obtain a notion of the accuracy of a test, we should estimate the true positive and true negative proportions. Mathematically this can be expressed as.

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

Precision: Precision Per cent of the correctly classified cases or samples with regards to the correctly classified cases as positives. The way to calculate the accuracy is as follows:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (2)$$

Recall: Recall is a metric used in ML to indicate the ability of a model to identify all the important examples of a particular class. It demonstrates the capacity of a model to explain the cases of a particular class. It is computed by the ratio of correct predictions of positive observations to the total positive observations.

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

F1-Score: The correctness of a ML model can be rated with the use of the F1 score. It combines the accuracy and the recall scores of a model. The accuracy measure gives the count of times, on the entire data set, that a model correctly guessed.

$$\text{F1 Score} = 2 * \frac{\text{Recall X Precision}}{\text{Recall} + \text{Precision}} * 100 (4)$$

mAP: One measure of quality and ranking is the Mean Average Precision (MAP). It examines the number of related recommendations and their position in the list. MAP at K = an average of the precision (AP) at K of all users or searches then multiplied by 100.

$$\text{mAP} = \frac{1}{n}\sum_{k=1}^{k=n} \text{AP}_k \qquad (5)$$

Table.1 Performance Evaluation Table – Classification

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| VGG16 | 0.89397 | 0.88300 | 0.90006 | 0.88870 |
| DenseNet | 0.92841 | 0.93054 | 0.92731 | 0.92870 |
| InceptionV3 | 0.92750 | 0.92830 | 0.92865 | 0.92839 |
| ResNet50 | 0.92252 | 0.92438 | 0.92280 | 0.92245 |
| Xception | 0.90847 | 0.90968 | 0.90993 | 0.90977 |
| ConvNeXt-Tiny | 0.94880 | 0.94920 | 0.94942 | 0.94920 |
| **Ensemble Model** | **0.92977** | **0.93082** | **0.93025** | **0.93047** |

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| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802245

Table.1 indicates the performance of various DL models in classifying things by various metrics of measurements.

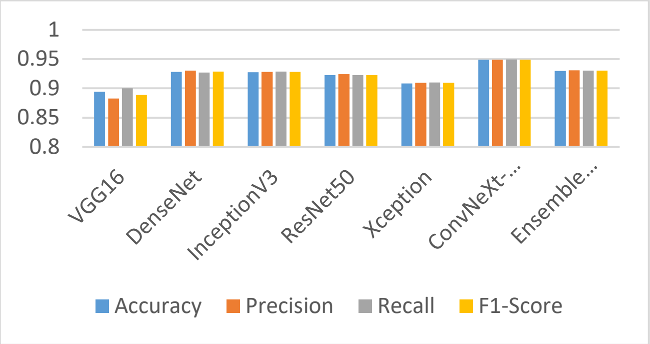


Fig.2 Comparison Graph – Classification

Figure 2 presents the measurements of success of various classification models with ConvNeXt being the most successful.

Table.2 Performance Evaluation – Detection

| **Model** | **Precision** | **Recall** | **mAP** |
|---|---|---|---|
| **YOLOv8** | **0.722** | **0.796** | **0.739** |
| YOLOv5s6 | 0.729 | 0.821 | 0.732 |
| YOLOv9 | 0.494 | 0.727 | 0.599 |
| YOLOv11 | 0.600 | 0.748 | 0.681 |

Table.2 Comparative success of models in detection in terms of precision, recall and mAP

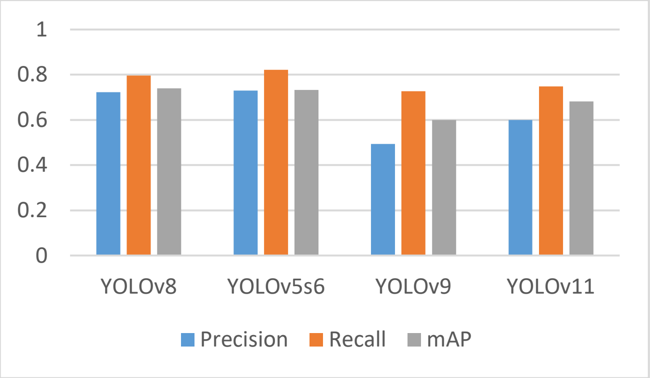


Fig.3 Comparison Graph – Detection

Fig.3 compares the models of detection, and YOLOv8 and YOLOv5s6 proved to be the leading models concerning accuracy and mAP.

## V. CONCLUSION

The findings of this paper indicate that the integration of object detection and DL-based classification technique of automated skin cancer analysis is effective. The test outcomes reveal that complex visual patterns in dermoscopic images can be identified by highly developed models of transfer learning, and it is possible to use them to make a correct diagnosis. The tested models revealed that the most accurate one was ConvNeXt-Tiny classifier (94.88%), and the values of precision, recall, and F1-score were above 94.9. This indicates its ability to distinguish between various kinds of skin diseases. YOLOv8 model was very good at locating and detecting lesions. It also obtained a mean Average Precision of 73.9, and 72.2 precision and 79.6 recall, which indicated that one could identify abnormal regions

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in the images. The inclusion of Grad-CAM helped to make the model more comprehensive as it focused on the areas that were different and influenced predictions. This increased the reliability of the model and simplified it to clinical use. What is more, the implementation of a Flask-based web application simplified end-to-end inference. Users were immediately provided with the capability to add images and obtain binding box vizualizations, anticipated disease classes and confidence scores. All in all, the findings indicate that combining the good classification models along with YOLO-based recognition that can be used successfully, the AI approaches that might be explained, and the interactive web interface is a helpful and scalable way to assist doctors in locating the skin cancer.

To enhance it in the future, the models can be made more stable and applicable in more centers with the help of training them on larger and more diverse datasets, which would involve other skin tones, imaging devices, and light conditions. Hybrid CNN transformer models and transformer-based vision systems can also be added to enhance classification and detection. You have an opportunity to look into fine-grained lesion segmentation to obtain precise border information on clinical assessment. Semi-supervised and self-supervised learning can also be utilized to utilise unlabelled data better and reduce the usage of annotations. It is possible that medical devices with limited resources can be employed by using real-time optimization and model compression techniques such as trimming and quantization. Continuous image analysis might also be added to monitor the worsening of the disease and identify it at the early stage.

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|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

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