iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70000

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Skin Disease Detection using Machine Learning

Sachin Bansal[1], Swanjal Gupta[2], Talha Pathan[3], Ansh Gangwar[4], Vansh Agarwal[5]
[1]Assistant Professor, [2, 3, 4, 5]Student, Department of Information Technology, JSS Academy of Technical Education, Noida, Uttar Pradesh

Abstract: Cancer is a serious illness due to someone's abnormal cell growth that can spread throughout the body. Although skin cancer is uncommon, it is still quite dangerous. Basal cell carcinoma, squamous cell carcinoma, and melanoma are the three main skin cancer types. In the U.S., melanoma is 1% of skin cancer cases, but it is the reason for the most skin cancer deaths. The American Cancer Society estimated that about 8,430 melanoma deaths will occur in 2025, 5470 of whom are men and 2960 are women. Fortunately, the death rates from melanoma are decreasing much more thanks to better treatments from 2013 to 2022. To effectively treat skin cancer, it should be detected early. When necessary, the diagnostic process usually begins with a clinical examination by a dermatologist, followed by a dermoscopy, then a biopsy, and a histopathological evaluation. These diagnostic steps can take several weeks in total. Many healthcare professionals argue that early diagnosis brings greater success. Machine learning algorithms can help detect skin cancer quickly, which can ultimately improve the prognosis of the patient.

I. INTRODUCTION

Cancer is a serious condition when cells keep on reproducing and invade other nearby tissues. Even if it is less common than other cancers, skin cancer is still deadly and therefore, it is fatal. Skin cancer truthfully refers to the group of cancers that develop in the skin Cells. Melanoma cases are rising more quickly than any other type of cancer, as per several reports. Melanoma represents only around 4% of all skin cancer incidents but is believed to cause around 75% of deaths from skin cancer.

Many research works are done using image processing and computer vision techniques to classify skin cancer into multiple categories for better detection. But, the previous models were built using small-size datasets such as a small number of dermoscopy images or low-resolution images. In previous studies, mostly ML based algorithms were used with KNN being the most commonly used algorithm for skin cancer classification. Integrating these machine learning models in detecting skin cancer can result in faster diagnosis and improve patient outcomes.

In contrast to previous studies, we utilized the ISIC_MSK-2 dataset, which includes 1535 images, using a CNN model with higher-resolution images for cancer classification.

A. Objectives

To study about skin cancer and related work. To develop a model for predicting skin cancer using high-resolution images.

To Automate the detection process using faster and more accurate image classification techniques.

To Minimize treatment time by improving the accuracy of disease prediction.

II. LITERATURE REVIEW

In a study referenced in [1], an innovative automated system for diagnosing skin diseases via color images was proposed, thereby negating the necessity for direct medical involvement. The system's operation is divided into two distinct phases. Initially, it detects infected skin using advanced color image processing techniques, such as K-means clustering and color gradient methodologies, aimed at precisely identifying the affected areas. Subsequently, the system classifies the specific type of skin disease utilizing artificial neural networks (ANNs). Evaluation of the system encompassed six different skin conditions, yielding an impressive average accuracy of 95.99% during the detection phase and 94.02% during the classification phase.

The authors in [2] introduced a novel model that leverages image processing techniques alongside Support Vector Machine (SVM) classification for melanoma detection. This method utilized the well-known ABCD rule for both detection and classification purposes. During the preprocessing phase, contrast enhancements were applied to increase brightness, succeeded by the application of the HSV (Hue, Saturation, and Value) color space for further image refinement. For segmentation, the GrabCut technique was employed to effectively isolate the affected area. The model achieved an accuracy of 80.00%, and to further enhance its performance, SVM was integrated to improve classification precision.

In [3], another approach for melanoma detection was proposed, targeting dermoscopy images by employing both image processing and machine learning techniques. This methodology comprised four essential stages: lesion segmentation, feature segmentation, feature extraction, and classification. Initially, the lesion segmentation phase focused on identifying and isolating the affected skin region for detailed analysis. This was followed by feature segmentation, during which critical characteristics of the lesion were extracted. The next stage, feature generation, processed these segmented features to prepare them for classification. Finally, in the classification phase, the system effectively categorized the lesion into its respective cancer type based on the extracted features, ensuring accurate detection of melanoma.

The domain used for skin lesion images includes that of chickenpox and measles (the case images presented here in between other infectious diseases will be from the paper [4] accompanying image of chickenpox, measles, and monkeypox), with most images also publicly sourced case reports, blogs, and news websites. In an effort to expand the dataset, data augmentation techniques were used and a 3-fold cross-validation experiment was performed. Diverse pre-trained DNNs, such as the VGG16, ResNet50, and InceptionV3, have been utilized to classify monkeypox and other diseases. In addition, we also developed an ensemble model with all three architectures combined. The classification accuracies achieved by VGG16, ResNet50, InceptionV3, and the ensemble model were 81.48% (±6.87%), 82.96% (±4.57%), 74.07% (±3.78%), and 79.26% (±1.05%), respectively.

In Paper [5], the authors performed skin lesion classification using machine learning algorithms and validated PH2 dataset which includes 200 dermoscopy images in which each image contains 768x560 pixel resolution and RGB color channels. Four various machine learning methods were used to classify the lesions: ANN method, SVM method, KNN method and DT method. Classification models were used to assess skin lesion.

The skin diseases classification system which uses MobileNetV2 and LSTM for improving prediction accuracy was designed by Kshirsagar et al. [6]. The main aim of this approach was to increase the reliability of skin disease predictions while effectively capturing state information for accurate forecasting. They also made a comparison with the traditional models like CNN and FTNN which shows that the proposed model performs better in skin disease classification and assessing tumor growth using the texture-based features.

In Paper [7], the authors presented a fast melanoma detection model using dermoscopic images through machine learning. The PH2 dataset, as used in their method, featured mainly through two approaches, namely extraction of features and classification. The researchers extracted relevant color and texture features and formed a 13-feature vector which had nine color features and four texture features. The database collected a 13-D feature vector for each dermoscopic image, which was labeled accordingly with its respective class. To classify the melanoma cases, the input features were provided to the Support Vector Machine (SVM) classifier which has the ability to classify melanoma images from all others.

The authors of [8] proposed an advanced method for melanoma detection using a Multiclass Support Vector Machine (MSVM). In their approach, first, input images were analyzed, then grouped and finally classified based on which melanoma had the highest probability for that image. Test samples were compared with training samples in the MSVM classification algorithm and assigned a probability value to the best-matched training group. The image database consisted of five types of melanoma that were used for testing and classification. Results from our simulation indicate that the One-Against-All MSVM classification method produced better accuracy than other techniques. To improve the classification accuracy and limitation of accuracy, K-means clustering segmentation was applied which enhanced the working of the overall system melanoma detection system.

In [9], a model of scaling learning that is semi-supervised and self-advised was presented for automated detection of melanoma using dermoscopic images. To improve accuracy of the classification, they implemented the self advised SVM algorithm to reduce the impact of misclassified data. The model was tested on 100 dermoscopic images and then compared against various other popular classification techniques. The findings showed the deep neural processing-based approach was more efficient than popular KNN, ANN, SVM-based and other EM, Transductive SVM-based semi-supervised techniques. The model was experimented for a melanoma with an accuracy of 89%.

In Paper [10], the authors designed a melanoma detection system which examines normal images of the affected skin. To spot potentially cancerous lesions, the authors used the ABCDE rule for melanoma detection. GrabCut was used to segment the input image and separate the lesion from the image. After isolating the lesion from the input, we then apply the importance of the lesion i.e. colour, shape and other geometric properties were extracted using image processing techniques. The extracted features were classified by a Support Vector Machine (SVM) with a Gaussian Radial Basis Function (RBF) kernel as malignant (cancerous) or benign (non-cancerous). Statistical analysis statistics showed that only six extracted features were sufficient for melanoma detection with 86.67% accuracy.

An image processing technique to detect skin disease models was proposed by Jagdish et al. [11]. They used fuzzy clustering on 50 sample images and classified the results using K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) schemes combined with wavelet analysis. According to the results KNN was able to achieve an accuracy of 91.2% over SVM. It also had a better classifier to detect skin disease. The classification techniques successfully managed to identify the type of skin disease. However, the dataset was small, limited to only 50 images and it included only 2 categories.: basal cell carcinoma and squamous cell carcinoma.

III. TOOLS AND TECHNIQUES USED

A. Python

Python is a very flexible, high-level programming language and is heavily used in fields including AI and machine learning. Python was first released by Guido van Rossum in 1991 and is currently maintained by the Python Software Foundation.

One of the main appeals of Python is its readability, and is an objective of the language to produce clean and organized programming code regardless of the operating system being used. In Python, indentation, and not braces, defines the structure of the code; this decision is part of a greater philosophy of simplicity and clarity. This philosophy is clearly expressed throughout the official Python website, and is assimilated throughout many programming environments.

Python provides an enormous standard library and third-party modules that come with Python functions that can be used to do all kinds of things like data processing, numerical computing, machine learning, data visualization, etc. Today, due to its versatility and strong community backing, Python finds itself in deep learning and artificial intelligence in software development.

B. Libraries in Python

Python has a vast array of robust libraries that make data handling, machine learning, and visualization easy. Some of the most important libraries utilized in this project include:

1) NumPy: A basic and necessary package for numerical computation in Python, allowing the support of n-dimensional arrays, big matrices on which we can perform matrix operations.
2) Keras: A high-level deep-learning API on top of tensorflow to make the building and training on neural networks easy.
3) Pandas: A popular data analysis and manipulation library providing data structures like Dataframes that are easy to use to manipulate data.
4) Matplotlib: A python plotting library that makes high quality plots and graphs for many types of publications.

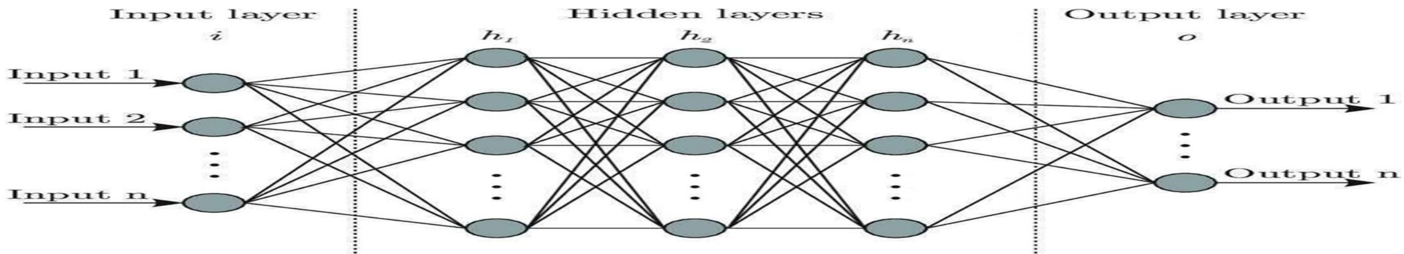
These libraries play an important role in implementing machine learning models, handling large datasets, and visualizing results effectively.

C. Neural Network

Neural networks are computer programs that simulate the structure and operations of the human being's brain. Neural networks are used in pattern recognition and making intelligent decisions due to input data. Neural networks carry out operations on data in a node network (neurons) in layers in the form of connections. Neural networks consist of:

1) Input Layer – Accepts raw input data (e.g., images, text, numbers).
2) Hidden Layers – Employ and restructure the input by propagating it through a series of computational operations.
3) Output Layer – Generates the final decision, prediction, or classification.

The networks are used heavily in clustering, classification, regression, and in pattern recognition too.



D. Convolutional Neural Network

A type of specialized deep neural network is the convolutional neural network (CNN or ConvNet), which is used extensively for image recognition and processing.Ir is a deep,feed-forward artificial neural network that possesses the ability to learn automatically and extract features from input data. Feed-forward neural networks,

They help discover patterns in images, text, speech, and time-series data by transforming real-world inputs into numerical vectors. The ability of neural networks to learn and adapt automatically makes them a core component of modern machine learning and artificial intelligence technologies.

Here, neural networks are utilized for classification of skin disease using dermoscopic images. The system utilizes deep learning to extract salient features from images and classify them according to learned patterns in training data. Neural networks are also a building block for advanced reinforcement learning, classification, and regression models for further enhancing accuracy and efficiency of computerized detection of skin disease.

Through the use of Python, its strong libraries, and neural networks, this project ensures a cost-effective and scalable method of detection of skin diseases, improving early detection and treatment options in the medical sector. also known as multi-layer perceptrons (MLPs), are deep networks that are behind most potent neural architectures. CNNs are being referred to as feed-forward networks because of one-way information flow, i.e., input to output and not back into the system. Unlike recurrent neural networks, CNNs lack feedback loops where outputs are used to compute the subsequent inputs.

These networks were modeled from the human visual cortex, a group of specialist neurons detecting and responding to various regions of the visual field. This was further built upon by Hubel and Wiesel in 1962 when, in studying the visual cortex, they found that some neurons oly fire in response to particular visual patterns, like vertical or horizontal edges. Their work depicted that these neurons were in an ordered columnar array, all of which when combined allowed them to perceive. This idea, where a specialist element specializes in something different, is one utilized in CNNs, and it allows them to efficiently analyze and identify visual patterns.

CNNs are currently a groundbreaking development in computer vision, surpassing traditional image processing techniques consistently. They have achieved remarkable success in real-world applications, including image classification, segmentation, object detection, and face recognition. Additionally, vision systems based on CNNs are also widely applied in autonomous vehicles, enabling self-driving cars to detect objects, read signs, and navigate around their environment with unprecedented precision.

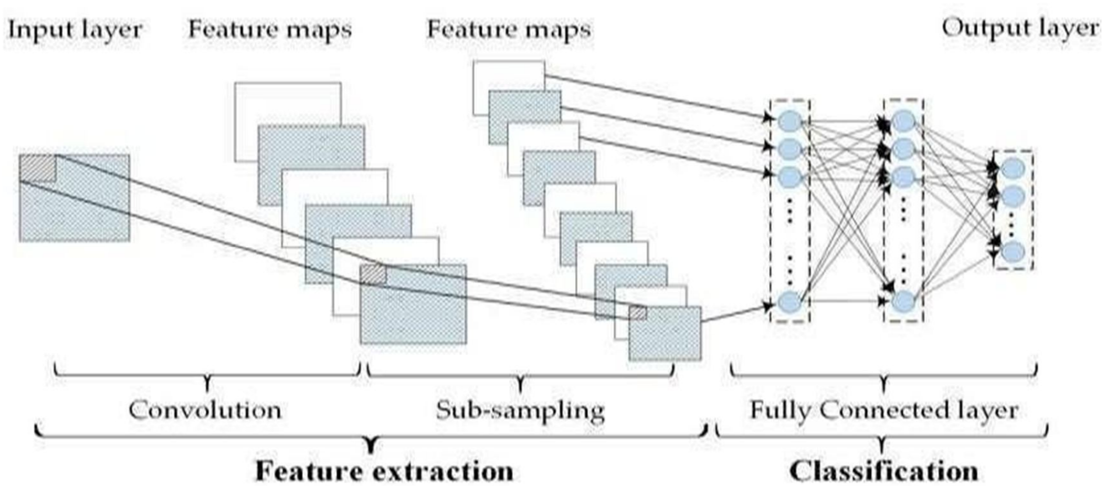


FIG 2: Convolutional Neural Network

E. VGGNet 16

Black GPUs..

VGG16 is a convolutional neural network (CNN) architecture developed by University of Oxford researchers K. Simonyan and A. Zisserman and described in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition." It was a very popular model submitted to ILSVRC-2014. The model also achieved a test accuracy top-5 on ImageNet, a database with over 14 million images and 1,000 categories, of 92.7%.

This network is renowned for its organized simplicity through the utilization of 3×3 convolutional layers in an iterative depth-addition pattern. Max pooling layers are utilized in order to shrink spatial dimensions, with the fully connected layers comprised of two layers with 4,096 nodes, followed by a softmax classifier. VGG16 training took weeks and was performed on NVIDIA Titan

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

F. ResNet 50

In ILSVRC 2015, Kaiming He et al. proposed Residual Neural Network (ResNet), which consisted of a new architecture with skip

The following illustration represents the VGG16 architecture.

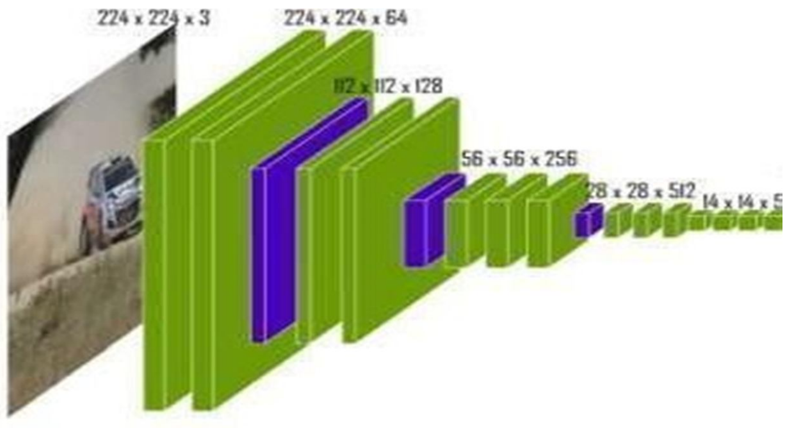


FIG 3 : VGGNet 16

connections and dense batch normalization. These skip connections, or gated units or gated recurrent units (GRUs), are similar to advanced units found in recurrent neural networks (RNNs). This approach enabled the training of a 152-layer deep neural network without any difficulty, with fewer complexities compared to VGGNet. ResNet achieved a top-5 error rate of 3.57%, which was higher than human-level accuracy on the data set. Despite being significantly deeper than VGG16 and VGG19, ResNet is more efficient in model size. This is primarily due to the fact that it employs global average pooling instead of fully connected layers, reducing the model size overall to 102MB for ResNet50.

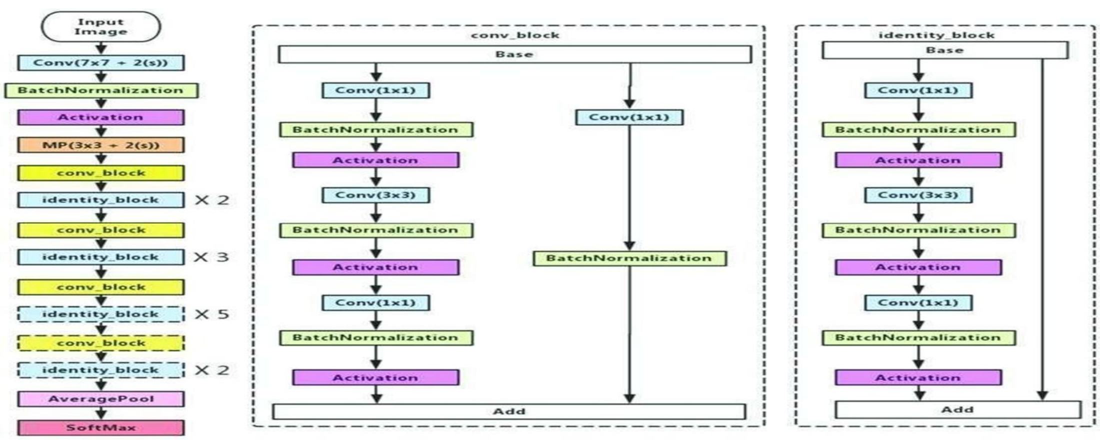


FIG 4: ResNet 50

IV. METHODOLOGY

A. Dataset Description

The dataset includes 1,535 dermatoscopic images, published openly in the ISIC archive as an academic machine learning training set. The benchmark dataset is available for machine learning usage as well as comparison against expert human diagnoses. The images were from several populations through several imaging modalities.

Due to this variation, different cleaning methods were applied, and a semi-automated neural network was specifically trained to process the data.

The dataset represents a broad spectrum of pigmented lesion diagnosis. Over half of the cases have been verified through pathology, while the remaining cases were confirmed using follow-up assessments, expert consensus, or in-vivo confocal microscopy.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

B. Dataset Details

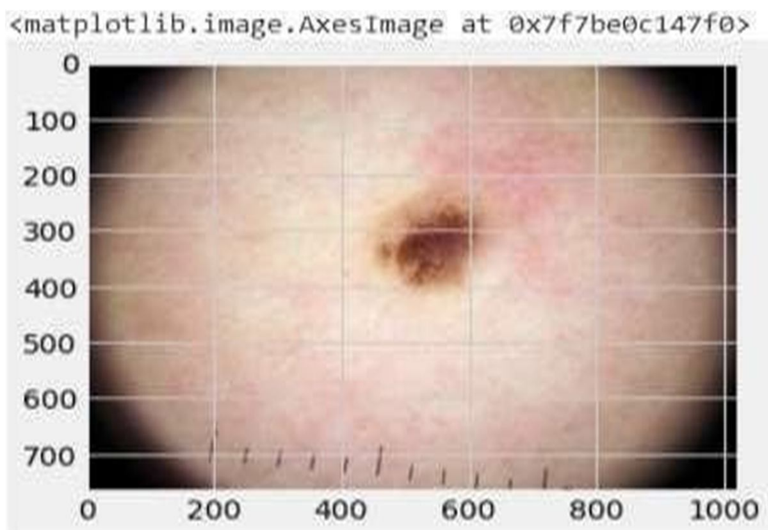
ISIC_MSK-2: It Contains both benign and malignant skin lesions, including biopsy-confirmed melanocytic and non-melanocytic conditions.

- Benign: 1,167 images
- Malignant: 352 images
- Indeterminate/Other Categories:
  Excluded from use
- Total Usable Images: 1,519
- Image Dimensions: 1024 × 768 pixels As summary the total images to use are:

Benign Images	Malignant Images
1167	352

Number of images used for training the classifier:1215 (80%) Number of images used for testing the classifier: 304 (20%) Some sample images are shown below:

1.Sample image of benign moles:



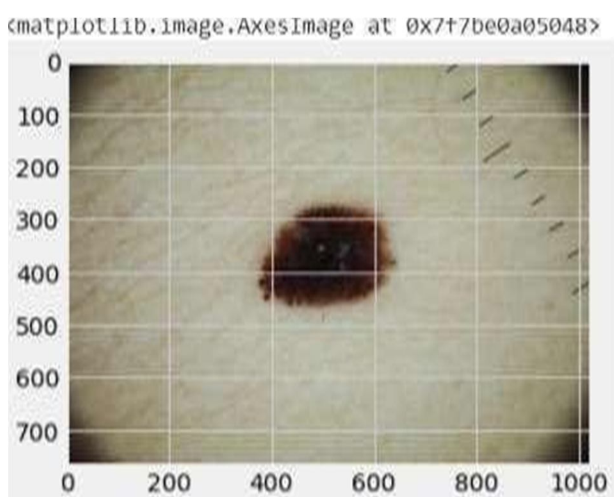


Fig 5: Sample image of malignant moles

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

C. General Architecture of Model

The proposed model helps dermatologists by examining images of moles and predicting the malignancy risk. We created a Convolutional Neural Network (CNN) model that automates the diagnosis with or even better than existing practices. We trained the model on 1,535 images to benchmark its performance with skilled doctors and compare how different the output is.

In the next steps, we will explain the development of the model, provide the final outcomes, and compare its performance with various models.

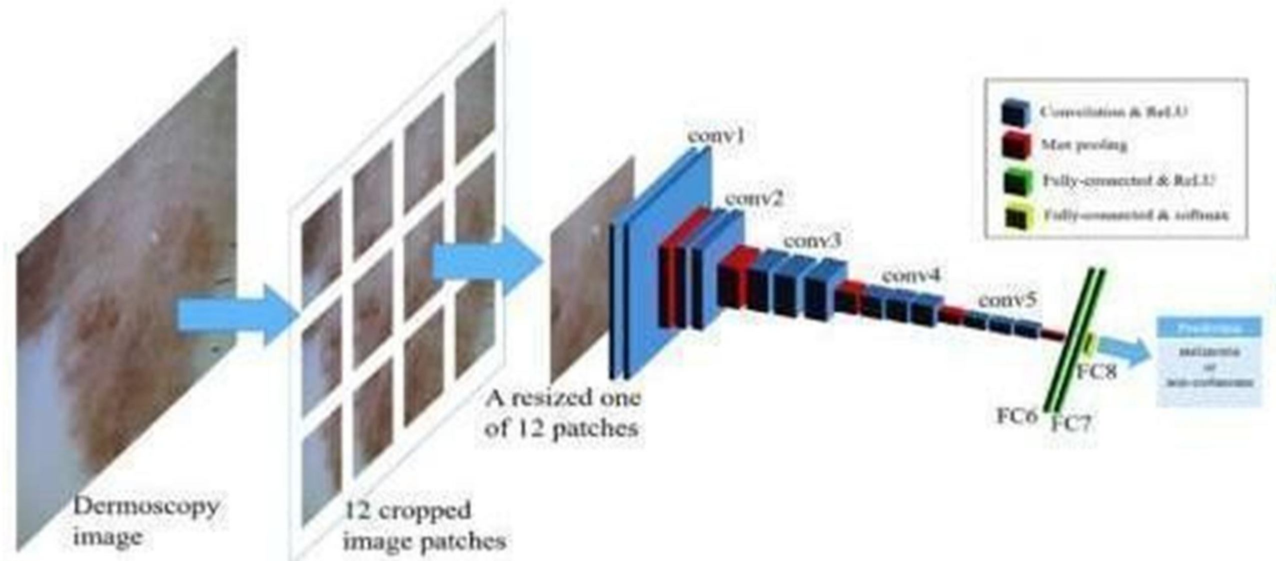


Fig 6: Schematic overview of CNN architecture

The dataset consists of two primary types of skin lesions: benign and malignant. Proposed model uses the ISIC_MSK-2 dataset and is processed on a GPU.

D. Proposed Approach

Figure 4.4 illustrates the program's workflow, outlining the various stages involved in model development, prediction, and preprocessing techniques.

E. Preprocessing Importing Essential Libraries

These libraries include Matplotlib, Numpy, Pandas, Sklearn and Keras.

F. Label Encoding

The data is cleaned by removing invalid and null values from the image label CSV file. In this instance, invalid labels such as 'indeterminate,' 'NaN,' 'indeterminate/benign,' and 'indeterminate/malignant' are removed. Once the images are loaded into memory, various transformations such as rotation, width shift, height shift, resizing, shearing, zooming, and horizontal flipping can be applied to obtain diverse views. In the current system, however, only image scaling is done because other transformations may alter the image in a way not suitable for input processing.

G. Exploratory data analysis (EDA)

This step helps one visualize and understand the dataset through the observation of its characteristics, distribution, and numerical results. The data is examined to observe its classification and how it is distributed across different categories.
The images are converted into a NumPy array, and the corresponding CSV file is labeled into two distinct classes: 0 for benign and 1 for malignant.

H. Loading & Resizing of images

The images are loaded into the img column and resized.

I. Train Test split

The data is split into training and testing sets in the 80 and 20 divisions respectively.

J. Model Building

The model is constructed using the keras sequential API, with the layers one after the other being added in sequence from the input layer. CNNs are different from other neural networks because of their systematic methodology, which conforms to these four steps: Convolution → Pooling → Flattening → Fully Connected Layer.
The process involves:

- Taking an input image.
- Applying filters or feature maps to generate a convolutional layer.Using feature maps or filters to construct a convolutional layer.
- Adding non-linearity through a rectifier function
- Pre-treatment of the image during the pooling phase.
- Performing pooling to create a pooled feature map.
- Flattening the feature map pooled earlier before inputting it into an artificial neural network.

K. Setting Optimizer and loss function

Finally, we compile the model with Adam optimizer and the binary cross-entropy loss function — this function measures the error rate between actual labels and predicted labels. This is useful for assessing how well the model performs on images with known classes.

L. Fitting the model

The dataset is divided into training and testing sets for model fitting. The model is then trained using the training set and validated using the testing data. The default batch size for 40 epochs is used for the training of the model. After training, we calculate accuracy and loss to calculate the efficiency of the model.

$$Accuracy = \frac{truepositive + truenegatives}{totalexamples}$$

$$L(y,\hat{y}) = -\sum_{j=0}^{M}\sum_{i=0}^{N}(y_{ij} * log(\hat{y}_{ij}))$$

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

M. Further Enhancements

To enhance the model's performance and compare it with existing image classification techniques, transfer learning is utilized. Pretrained convolution layers from different ImageNet datasets are incorporated. Convolutional models such as VGGNet16, VGGNet19, ResNet50, Xception, and InceptionResNetV2 are used, with selected layers frozen. The dense layer of these pretrained models is replaced with a custom dense layer and trained using the ISIC_MSK-2 dataset to improve classification accuracy.

V. RESULTS AND OBSERVATION

A dataset consisting of 1,535 images (each of size 1024×768) is used, split into 1,215 images for training and 304 images for validation. The images are resized based on the underlying model into three resolutions: 128×128, 256×256, and 512×512. A CNN model is constructed and trained using the training data, which is then sized up against the performance of other image classification models that leverage transfer learning methodologies on the identical dataset. The iterations picked based on accuracy loss trends for each model are:

- CNN: 20 iterations
- VGG16 & ResNet50: 10 iterations

Validation uses 304 images from the validation set. Three models are compared to check their performance at different image resolutions. Tables 5.1 and 5.2 show accuracy and loss comparisons of all models trained on the ISIC_MSK-2 dataset, tested on both its training and testing partitions.

A. Comparison of Results on Training Dataset

After looking at the results, ResNet50 gets the best training accuracy at 0.9613 for the 256×256 resolution.

S. No.	Model Used	Resolution	Loss	Accuracy
1.	CNN	128 x 128	0.4923	0.7770
2.	CNN	256 x 256	0.4857	0.7901
3.	CNN	512 x 512	0.5381	0.7712
4.	VGGNet16	128 x 128	0.2715	0.8889
5.	VGGNet16	256 x 256	0.1903	0.9267
6.	VGGNet16	512 x 512	0.1546	0.9432
7.	RESNet50	128 x 128	0.2743	0.9012
8.	RESNet50	256 x 256	0.1890	0.9613

Table 1: Model Evaluation: training dataset

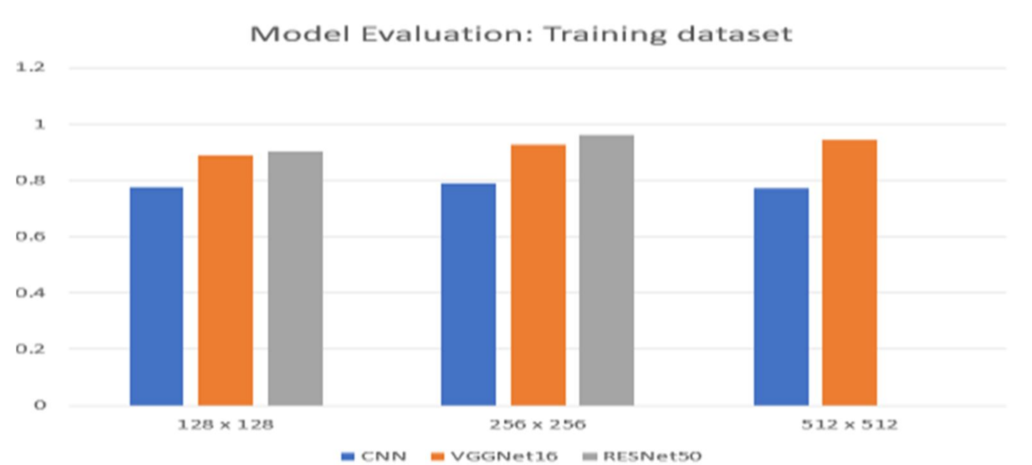


Fig 7:Training Accuracy comparison of CNN, RESNet50 and VGGNet16

B. Comparison of results on validation dataset

After comparing results, we can say that highest training accuracy for resolution 128x128 is obtained by VGG16, which is 0.8191

S. No.	Model Used	Resolution	Loss	Accuracy
1.	CNN	128 x 128	0.4690	0.7928
2.	CNN	256 x 256	0.5365	0.7895
3.	CNN	512 x 512	0.5553	0.7566
4.	VGGNet16	128 x 128	0.4716	0.8191
5.	VGGNet16	256 x 256	0.5122	0.7928
6.	VGGNet16	512 x 512	0.6067	0.7664
7.	RESNet50	128 x 128	1.1297	0.7829
8.	RESNet50	256 x 256	0.5478	0.7632

Table 2: Model Evaluation: Validation dataset

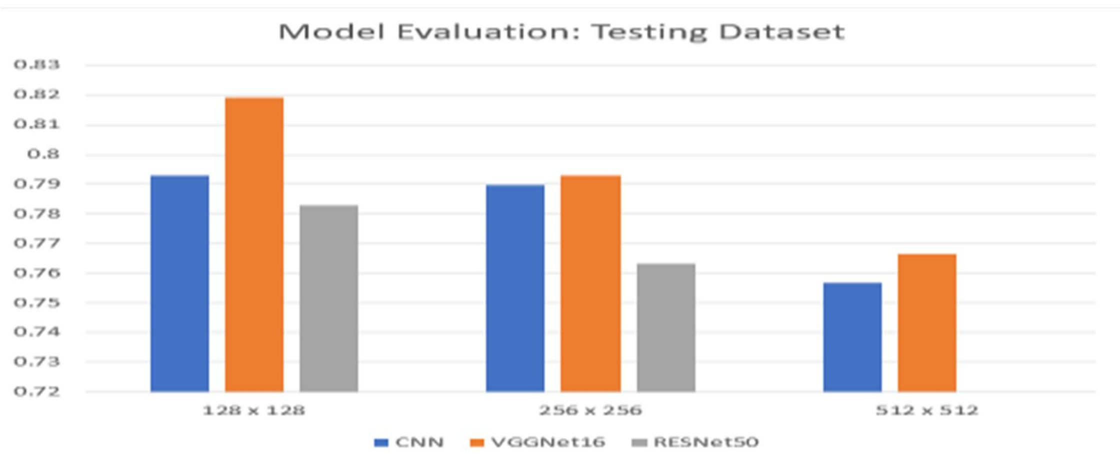


Fig 8: Validation Accuracy comparison of CNN, RESNet50 and VGGNet16

VI. CONCLUSION AND FUTURE SCOPE

This work tries to help patients spot skin cancer by using automated prediction with neural networks, so they don't have to go to the hospital right away. Different models, like ResNet50, CNN, and VGGNet16 were used for classification. VGGNet16 got the best accuracy of 81.91%. The way this model works can be improved by tweaking hyperparameters or making the dataset larger with more samples. Also, trying out different pooling methods, architectures, and optimizers can lead to big changes in how well the model works. Data augmentation techniques may be applied in future works to address class imbalance and promote generalization. Further, an exploration of more advanced deep learning architectures accompanied by ensemble learning would likely lead to the further optimization of accuracy in skin cancer detection.

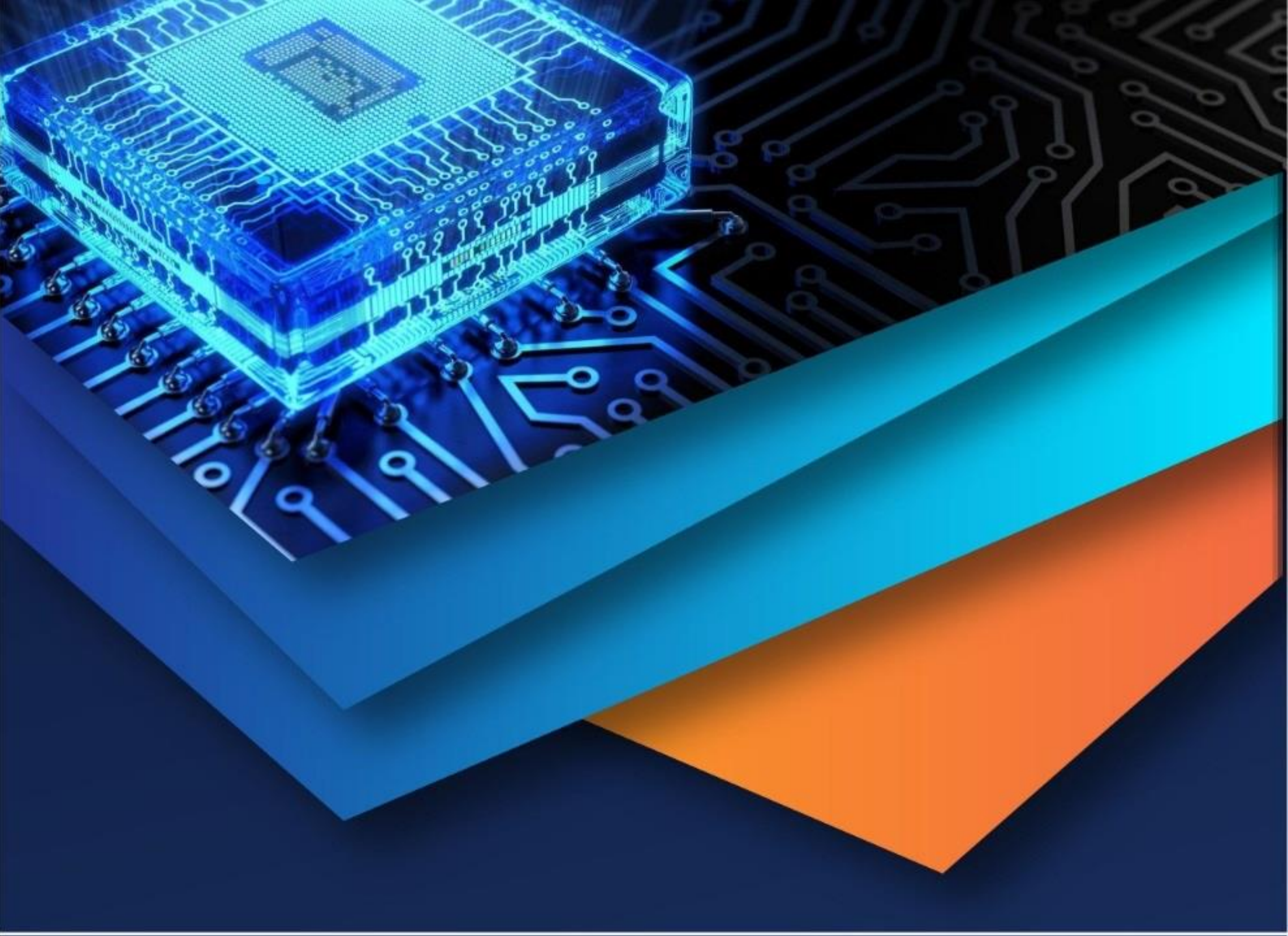
REFERENCES

[1] Kibria, G., Firoze, A., Amini, A., & Yan, H. (2012) "Dermatological Disease Diagnosis Using Color-Skin Images." Xian: International Conference on Machine Learning and Cybernetics.
[2] S. Mustafa, A. B. Dauda, and M. Dauda,―Image processing and SVM classification for melanoma detection,‖ 2017 InternationalConference on Computing Networking and Informatics (ICCNI), 2017.
[3] M. E. Celebi, H. A. Kingravi, Y. A. Aslandogan, and W. V. Stoecker,―Detection of blue-white veil areas in dermoscopy images using machine learning techniques,‖ Medical Imaging 2006: Image Processing, Feb. 2006.
[4] Ali, S. N. et al. Monkeypox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study, Comput. Vis. Pattern Recognit., pp. 2–5, [Online]. Available: (2022). http://arxiv.org/abs/2207.03342
[5] I.A. Ozkan and M. Koklu, ―Skin Lesion Classification using Machine Learning Algorithms,‖ International Journal of Intelligent Systems and Applications in Engineering, vol. 4, no. 5, pp. 285–289, 2017.
[6] P.R. Kshirsagar, H. Manoharan, S. Shitharth, A.M. Alshareef, N. Albishry, P.K. Balachandran, Deep learning approaches for prognosis of automated skin disease, Life 2022 12 (426) (2022).

[7] Z. Waheed, A. Waheed, M. Zafar, and F. Riaz,―An efficient machine learning approach for the detection of melanoma using dermoscopic International images,‖ 2017 Conference on Communication, Computing medicine and Biology Society (EMBC), 2016.
[8] R. S. S. Sundar and M. Vadivel,―Performance analysis of melanoma early detection using skin lesion classification system,‖ 2016 International Conference on Circuit, Power and Computing Technologies (ICCPCT), 2016.
[9] A. Masood, A. A.-Jumaily, and K. Anam,―Self-supervised learning model for skin cancer diagnosis,‖ 2015 7th International IEEE/EMBS Conference on Neural Engineering (NER), 2015.
[10] S. Mustafa and A. Kimura, ―A SVM-based diagnosis of melanoma using only useful image features,‖ 2018 International Workshop on Advanced Image Technology (IWAIT), 2018.
[11] Jagdis etal., J.A.D.L. Cruz-Vargas, M.E.R. Camacho, Advance study of skin diseases detection using image processing methods, Nat. Volatiles Essent. Oils J. 9 (1) (2022) 997–1007.
[12] www.medium.com

Data Citation

[1] https://www.isic- archive.com/#!/topWithHeader/onlyHeaderTop/ gallery



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY