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Machine Learning Mastery: Leveraging Convolutional Neural Networks to Classify Skin Cancers as Benign or Malignant in the ISIC Database

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Abstract : This research tackles the urgent need for enhanced precision in the detection of skin cancer, a common yet potentially deadly disease. Traditional diagnostic techniques frequently fall short in accuracy, prompting unnecessary and invasive medical interventions. Previous attempts to employ machine learning for distinguishing among different types of skin cancer have not been fully successful in achieving effective differentiation. To address these challenges, the study proposes an innovative approach utilizing Convolutional Neural Networks (CNN) for the autonomous identification of skin cancer. The designed CNN architecture incorporates three hidden layers, with the number of channels in each layer progressively increasing from 16 to 32, and then to 64. The model leverages the AdamW optimization algorithm with a learning rate set at 0.001, a choice that has proven to be highly effective. In evaluations conducted using the International Skin Imaging Collaboration (ISIC) dataset, which involved classifying skin lesions as either benign or malignant, the proposed CNN methodology demonstrated a remarkable accuracy rate of 96%. This level of precision indicates a significant advancement in the field of skin cancer diagnostics, highlighting the potential of CNN-based models to revolutionize the early detection and treatment of this condition.

Keywords : Convolutional Neural Networks , ISIC database , Skin Cancers , Hidden Layers, Benign, Malignant, Machine Learning.

1. Introduction

In the realm of dermatological diagnostics, the early and accurate detection of skin cancers stands as a critical juncture that can significantly influence patient outcomes. "Machine Learning Mastery: Leveraging Convolutional Neural Networks to Classify Skin Cancers as Benign or Malignant in the ISIC Database" delves into the transformative potential of advanced computational models in medical imaging.

The thrust of this exploration is anchored in the application of Convolutional Neural Networks (CNNs), a class of deep neural networks renowned for their proficiency in analyzing visual imagery. CNNs emulate the intricate processing of the human brain, allowing for the automated detection of complex patterns within imaging data. The architecture of these networks is particularly adept at

handling the spatial hierarchies in images, which is pivotal when discerning subtle dermatological nuances that demarcate benign from malignant skin lesions.

The backbone of our investigation lies within the rich reservoir of the International Skin Imaging Collaboration (ISIC) database—a comprehensive collection of skin lesion images designed to spur technological advancements in the field. By employing CNNs equipped with multiple hidden layers, our study aims to harness the depth and variety of features present within the ISIC database to advance the field of automated skin cancer classification.

These hidden layers, each a convolutional stratum of neurons, work in concert to filter and distill image characteristics, capturing edges, textures, and patterns integral to the identification of malignancies. As the information passes through these layers, it undergoes a transformation—what begins as raw pixel data emerges as a nuanced understanding of the lesion's morphology.

The objective is twofold: to push the boundaries of machine learning within dermatology and to refine the precision with which these neural networks can differentiate between benign and malignant skin

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cancers. In achieving high accuracy, we not only pave the way for more reliable diagnostic tools but also provide a beacon for future research—a testament to the synergy between artificial intelligence and medical expertise in combating skin cancer.

In recent years, there has been a significant increase in the incidence of skin cancer, making it one of the most rapidly expanding forms of cancer [1]. Being the largest organ, the skin is naturally more susceptible to cancer [2]. The two primary categories of skin cancer are melanoma and nonmelanoma [3, 4]. Melanoma, particularly challenging to diagnose and highly lethal, accounts for about 1% of skin cancer cases but has a disproportionately high mortality rate, as reported by the American Cancer Society [4]. It primarily targets melanocytes - cells that produce melanin. Its origin is often linked to abnormal growth in otherwise normal melanocytes and can occur anywhere on the body. Commonly, it appears in areas frequently exposed to the sun, like the hands, face, neck, and lips. Early detection of melanoma is crucial; if undiagnosed, it can metastasize, leading to fatal outcomes [5]. The primary sites of genesis for these malignancies are mostly located within the intermediate to superficial layers of the epidermis. Of the options presented, BCC is the prevailing

choice [6]. In contrast to melanoma, non-melanoma skin tumours have a lower propensity for metastasis. The correlation between sun exposure and the likelihood of acquiring skin cancer is significant [7]. There is an increased likelihood of skin cancer developing in areas of the body that are consistently exposed to solar radiation, such as the head, face, lips, ears, neck, torso, arms, hands, and legs, in females. On the contrary, there is evidence to suggest that males exhibit a greater susceptibility to developing skin cancer, particularly on the extremities of their hands and feet [8]. It is important to highlight that skin cancer, including melanoma, can develop in areas that are not frequently exposed to sunlight, such as the vaginal region, interdigital spaces, and palms.

1.1 Basal Cell Carcinoma Symptoms

- Common Sites: Typically appears on sun-exposed areas like the face and neck.
- Characteristics:
  - Pearlescent or viscous nodules.
  - Absence of brown or flesh-colored lesions that resemble scar tissue.
  - A recurrent open wound that scabs over, oozes, and reopens.

1.2 Squamous Cell Carcinoma Symptoms

- Frequent Occurrence: Commonly found on sun-exposed regions such as the face, ears, and hands. In individuals with darker skin, it often appears on less sun-exposed areas.
- Manifestations:
  - Firm, red nodules.
  - Scaly, crusty surface lesions.

1.3 Melanoma Symptoms and Indicators

- Occurrence: Can arise anywhere on the body, either as a new growth or changes in an existing mole. In men, it often occurs on the face and trunk, while in women, it is commonly found on the lower legs.
- Risk: Affects individuals of all skin tones. More prevalent in darker skin tones on palms, soles, under fingernails and toenails.
- Signs:
  - Dark spots on a brown base.
  - Mole changes, such as irregular borders and varying colors (red, pink, white, blue, black).
  - Itchy or painful lesions.
  - Dark patches or spots on palms, soles, digits, or mucous membranes.

1.4 Rare Skin Cancer Symptoms

- Kaposi's Sarcoma:
  - Begins in blood vessels, leading to skin or mucous membrane discoloration.
  - More likely in immunocompromised individuals, older males of Italian or Eastern European Jewish descent, and young African men.
- Merkel Cell Carcinoma:
  - Appears as hard, shiny nodules on or under the skin or in hair follicles, primarily on the head, neck, and trunk.

In this paper contribute proposed approach typically involves the use of sophisticated algorithms and neural network models, such as updated Convolutional Neural Networks (CNNs).

The rest of this paper is organized into a coherent structure to facilitate a clear and comprehensive understanding of our study on leveraging Convolutional Neural Networks (CNNs) for the classification of skin cancers using the ISIC database. The sequence is as follows:

First, Introduction: We begin by setting the stage with an introduction that outlines the significance and the pressing need for improved diagnostic methods in dermatology, especially for distinguishing between benign and malignant skin lesions. The introduction will provide a backdrop to the potential of machine learning in this domain, with a specific emphasis on the capabilities of CNNs.

Second, Review of Related Works: Following the introduction, we delve into a literature review that encapsulates previous studies and advancements in the field. This section is crucial for situating our work within the existing body of knowledge, highlighting the evolution of machine learning applications in skin cancer diagnostics and the use of the ISIC database in this context.

Third, Proposed Methods: After establishing a foundation with the review of related works, we detail the proposed methods. This section is dedicated to describing the architecture of the CNN used in our study, the rationale behind the selection of certain hyperparameters, and the preprocessing steps applied to the ISIC database images to optimize them for machine learning tasks.

Fourth, Implementation and Results: The implementation section provides an in-depth look at the practical aspects of our study, from the setup of the computational environment to the training of the CNN model. It concludes with the presentation and discussion of the results, comparing the model's performance in terms of accuracy, sensitivity, and specificity in classifying skin cancers.

Fifth, Conclusion: We conclude the paper with a summary of the findings and their implications for the field of dermatology. In this final part, we will reflect on the effectiveness of the proposed CNN model, consider the limitations of the current study, and suggest directions for future research that could build on our work and further improve the diagnosis and treatment of skin cancer.

2. Review of related works

A new portable gadget for non-invasive skin cancer screening, SkanMD, uses electromagnetic waves and radio frequency technologies. A sensitive electromagnetic sensor, customised circuitry, and machine learning algorithms are included. SkanMD identified malignant and non-cancerous lesions with over 92% sensitivity and 81.4% specificity in 46 people, including 18 with skin cancer. In addition to existing approaches, the gadget, which measures skin reflection coefficient S11, may improve patient comfort and speed up diagnosis [9].

The research emphasises the need of early and accurate skin cancer detection, a worldwide health concern, and addresses clinical assessment of skin lesions, such as extended wait times and subjective judgements. Deep learning improves diagnostic speed and accuracy, enabling early detection and relieving healthcare staff. The study presented a smart healthcare system and developed deep learning models for skin cancer classification to solve class imbalance and decision-making interpretation. The algorithm identified seven skin cancer types with 82% accuracy against six classifiers and the HAM10000 dataset. An explainable AI technology helped clinicians make early-stage diagnoses by providing greater insights into categorization judgements [10].

This research introduces a microwave reflectometry-based method for non-invasive, in-vivo skin cancer diagnostics and early detection. This procedure is relevant due to rising skin cancer prevalence and hospital delays. The technology detects dielectric differences between normal and pathological skin tissues using microwaves up to 3 GHz. To measure skin dielectric characteristics, it uses a truncated open-ended coaxial probe and a miniaturised Vector Network Analyzer. The technology distinguishes malignant and benign lesions and healthy skin on volunteer patients, presenting benefits in efficacy, cost-efficiency, compactness, comfort, and sensitivity [11].

A cutting-edge technique for early skin disease identification is introduced in this study to avoid skin lesion spread. Using CNN and LBP, the system uses characteristics from both architectures to improve accuracy. Trained and tested using a popular public dataset for skin cancer diagnosis, it classifies skin diseases. With 98.60% accuracy and 97.32% validation accuracy, the system is very effective. Comparative assessments of other designs reveal that this integrated method performs better [12].

The paper stresses the need of early skin cancer identification, a fast expanding disease with limited resources. It underlines dermatologists' early-stage detection issues and the need of deep learning, especially CNNs, which excel at object recognition and categorization. The research uses 10,015 MNIST: HAM10000 samples of seven skin lesions. Sampling, dull razor, and autoencoder segmentation are used for advanced data preprocessing. Training the model using transfer learning approaches like DenseNet169 and ResNet 50 shows how cutting-edge AI can fight skin cancer [13].

Skin cancer is one of the most frequent kinds of cancer, which is fatal. Traditional machine learning approaches for skin cancer diagnosis using human-engineered characteristics are laborious and time-consuming. This research uses convolution-based neural networks to automatically extract characteristics from the ISIC public dataset to identify skin cancer. It highlights the limits of individual machine learning models and suggests ensemble learning to increase cancer diagnosis accuracy, sensitivity, specificity, F-score, and precision by integrating VGG, CapsNet, and ResNet choices. This ensemble approach's higher performance in the research shows it might identify additional disorders [14].

Computer vision is crucial to disease identification, especially early-stage skin cancer diagnosis. Two novel approaches categorise dermoscopic pictures into benign and malignant tumours. The first technique extracts features using KNN and pretrained deep neural networks. Second, AlexNet is optimised using a grey wolf optimizer for better performance. Neural network models and other machine learning (ML) and deep learning (DL) methods for skin cancer picture categorization are also examined. On 4000 photos from the ISIC archive dataset, some strategies outperformed others, with some models reaching 99% accuracy. This innovation in computer-aided diagnostic tools improves skin cancer detection and categorization [15].

This work develops a genetic programming-based computer-aided skin cancer diagnosis method utilising photographs. GP grows models with a flexible representation, picking and building features better than classical machine learning. The two-stage GP technique identifies critical traits and then creates additional ones to improve classification. This approach uses pyramid-structured wavelet decomposition and local binary patterns to include varied picture attributes. This GP method outperformed traditional classification algorithms on two real-world skin picture datasets. GP models are interpretable, helping dermatologists detect skin cancer diagnostic characteristics [16].

This research emphasises the necessity of early skin cancer diagnosis and the difficulties of recognising malignant tumours in dermatoscopic pictures. The article presents FixCaps, an upgraded capsule network for dermatoscopic image categorization, to overcome these concerns. In FixCaps, the lowest convolution layer has a 31x31 kernel size, resulting in a bigger receptive field than the normal 9x9. This architecture with a convolutional block attention module prevent spatial information loss. To avoid capsule layer underfitting, group convolution is used. FixCaps outperforms other approaches in detection accuracy and processing performance. In HAM10000 testing, FixCaps surpassed IRv2-SA in skin cancer detection with 96.49% accuracy [17].

Skin cancer, caused by aberrant skin cell formation, must be diagnosed early to avoid dangerous types like melanoma and focal cell carcinoma. Early skin cancer screening is expensive and complicated, thus the research proposes a deep learning solution. A cascaded ensemble network using ConvNets and handmade features in a multi-layer perceptron architecture is proposed. ConvNets extract sophisticated, non-handcrafted visual characteristics and manually designed elements like colour moments and textures in this model. The ensemble deep learning model's accuracy improved from 85.3% to 98.3%, making early skin cancer categorization more efficient [18].

This overview discusses overparameterized models' inefficiency in skin cancer detection using advanced neural network architectures. Recent studies imply polynomially smaller hidden unit networks perform better. This paper describe a multistage unit-vise deep dense residual network with transition and supervision blocks to improve feature representation. This network has numerous stages with tightly linked residual units, unlike ResNet. Due to its local consideration of elements from prior levels, this architecture simplifies the network. This novel solution outperformed existing approaches and the best state-of-the-art on the ISIC-2018 challenge with 10,015 training photos at 98.05% accuracy. This Unit-vise network code is also public [19].

3. Proposed methods

Early detection is crucial in the treatment of skin cancer, as noted in reference [20]. Typically, the diagnostic process begins with a biopsy of the suspected skin area, aiming to obtain a tissue sample for further analysis to confirm whether the lesion is cancerous. This traditional method is often intricate and slow-paced. In contrast, computer-aided diagnosis of skin cancer offers a quick, simple, and cost-effective alternative. By employing a diverse range of non-invasive diagnostic techniques, it is feasible to ascertain whether the symptoms associated with skin cancer are indicative of melanoma or another variant of the disease.

3.1 Proposed Architecture

Figure 1 illustrates the conventional approach for detecting skin cancer, which consists of multiple processes. These steps are as follows: capturing the picture, preprocessing the image, segmenting the preprocessed image, extracting the essential features, and lastly classifying the image.

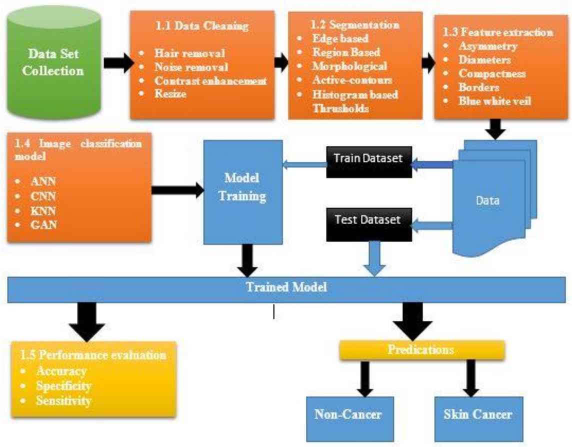

Figure 1: Diagram of the proposed procedure.

The figure 1 appears to depict a flowchart outlining a process for machine learning classification, specifically for cancer prediction. The process starts with data collection, followed by data cleansing which includes noise removal and contrast enhancement. Segmentation is next, with methods like region-based, model-based, and thresholding applied. Feature extraction follows, using algorithms to identify asymmetry, border irregularities, color, and structure. The process involves using different machine learning classification algorithms such as ANN, CNN, and SVM. After training the model with a train dataset and evaluating it against a test dataset, the performance is evaluated based on accuracy, specificity, and sensitivity. The final output is the predictions for new cancer and skin cancer cases.

3.2 Proposed CNN :

Each layer may include:

- Convolution operation. (applies a convolutional filter (kernel))
- Activation function (e.g., ReLU (Rectified Linear Unit)).
- Pooling operation (e.g., MaxPooling) to reduce dimensions.
- Define a loss function (e.g., binary cross-entropy for binary classification).
- Choose an optimizer (e.g., AdamW (Adaptive Moment Estimation weight decay regularization)).
- Fully connected (Dense) layers: Perform classification based on the extracted features.

Train dataset : 80 % images

Test Dataset : 20 % images

Predications : Skin Cancer or Other

Result evaluation : Accuracy (%) , Precision (%), Recall (%), Loss

3.3 Description of proposed algorithm

1. Convolution Operation

- **Purpose**: Extracts features from input data.
- **How It Works**: It applies a convolutional filter (kernel) to the input to create a feature map, capturing spatial hierarchies and patterns like edges, textures, or more complex patterns in deeper layers.

2. Activation Function

- **ReLU (Rectified Linear Unit)**:
  - The purpose of this approach is to include non-linearity into the model, so enabling it to acquire a deeper understanding of complicated functions.
  - The functioning of the system is as follows: if the input is positive, it is immediately outputted; however, if the input is negative, the output is zero.
- **Tanh (Hyperbolic Tangent)**:
  - **Purpose**: Similar to ReLU, but it outputs values between -1 and 1, which can be useful in certain contexts where normalization of data is required.

3. Pooling Operation

- **MaxPooling**:
  - The purpose of this operation is to decrease the spatial dimensions, namely the width and height, of the input volume in order to facilitate the computational processes.
  - The process involves the selection of the highest-valued element inside the specific area of the feature map that is included by the filter.
- **MinPooling** (less common than MaxPooling):
  - **Purpose**: Similar to MaxPooling, but it may preserve different features, like darker spots in image processing.
  - **How It Works**: It selects the minimum element from the region of the feature map.

4. Loss Function

- **Binary Cross-Entropy**:
  - The purpose of this metric is to assess the dissimilarity between two probability distributions, namely the true label distribution and the anticipated label distribution, in binary classification tasks.

- The process involves the computation of the cross-entropy loss, which measures the discrepancy between the predicted probability and the true binary labels.

5. Optimizer

- **AdamW (Adaptive Moment Estimation with Weight Decay Regularization)**:
    - **Purpose**: Optimizes neural network weights and minimizes the loss function.
    - **How It Works**: Combines the benefits of adaptive learning rate methods with weight decay regularization for better generalization.
- **Gradient Descent**:
    - **Purpose**: A more basic form of optimization, updating weights to minimize the loss function.
    - The functioning of the system involves updating the weights by using the gradient of the loss function in relation to the weights.

6. Fully Connected (Dense) Layers

- **Purpose**: After feature extraction and reduction, dense layers perform classification based on these extracted features.
- **How It Works**: Neurons in a dense layer have full connections to all activations in the previous layer, as seen in traditional neural networks. This layer is typically placed near the end of a CNN architecture to perform high-level reasoning and make final classification decisions.

4. Implementation and result

Explain explore an instance case of skin cancer in this part, highlighting the outcomes associated with the proposed work. This example underscores how our approach effectively identifies and classifies skin cancer types, providing a practical application of our research findings. Imagine a scenario where a patient presents with a suspicious skin lesion. Traditionally, this would require a dermatological examination, possibly followed by a biopsy, to determine if the lesion is cancerous. However, in our proposed methodology, we utilize advanced imaging techniques coupled with the power of artificial intelligence (AI), particularly Convolutional Neural Networks (CNNs), to analyze the lesion. Using high-resolution images of the patient's skin, our system processes these images through a pre-trained CNN model. This model, designed to recognize patterns and features indicative of various types of skin cancer, analyses the lesion's shape, size, color, and other distinctive features.

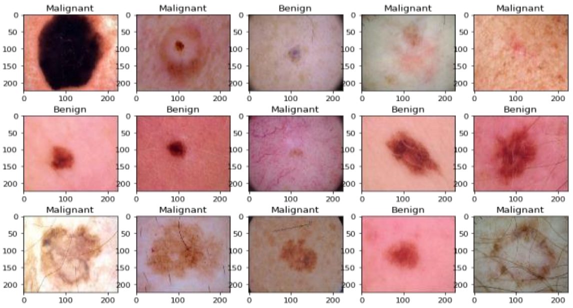

Figure 2: Sample of Dataset. [21]

The figure 2 displays a set of dermatological skin images labeled as "Malignant" or "Benign," showcasing various skin lesions that are likely being used for medical analysis, possibly in the context of skin cancer detection. There are more samples labeled as malignant than benign, indicating a variety in the appearance of malignant lesions in terms of color, shape, and size. This kind of visual data is typically used in machine learning models for training and validation purposes, allowing algorithms to learn to differentiate between benign and malignant cases based on visual patterns detected in the images.

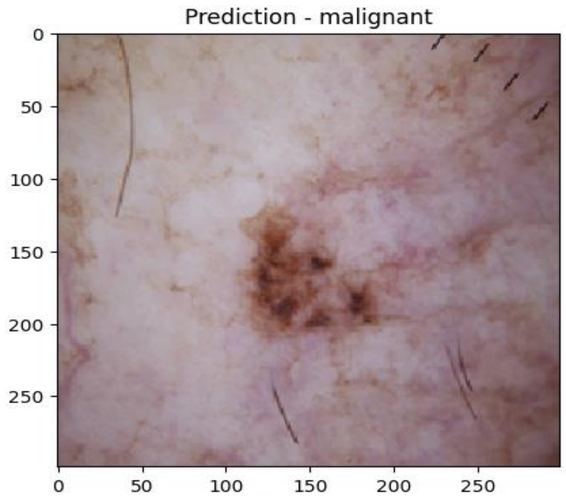

Figure 3: Shows model predication of malignant skin cancer.

The figure 3 shows a close-up view of a skin lesion with a label "Prediction - malignant" at the top, indicating that a machine learning model has likely analyzed the lesion and predicted it to be malignant. The grid overlay with coordinates on the axes suggests that this is a scientific or medical analysis context, possibly part of a dermatological study or the output of a diagnostic imaging system designed to detect skin cancer. The lesion itself has irregular pigmentation and borders, which are common characteristics associated with malignant skin tumors.

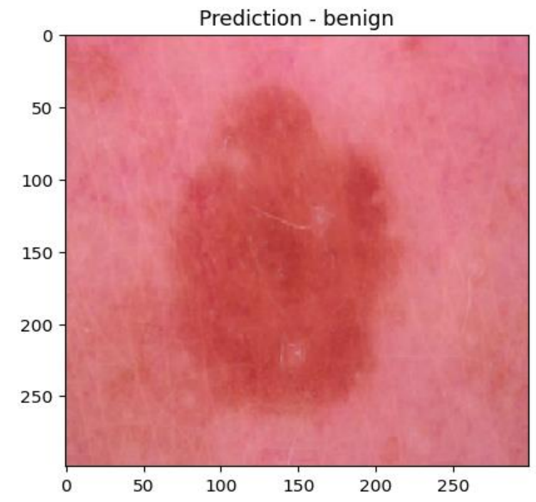

Figure 4: Illustrations predication of benign skin cancer.

The figure 4 shows a skin lesion with a label "Prediction - benign" at the top, suggesting that a machine learning algorithm has evaluated the lesion and determined it to be non-cancerous. The lesion is more uniform in color and has a smoother border compared to malignant ones, which are features that models often use to distinguish benign growths. The presence of the grid with coordinates suggests this is a medical image used for analysis, likely part of a dataset for training or testing a dermatological diagnostic tool focused on identifying skin conditions.

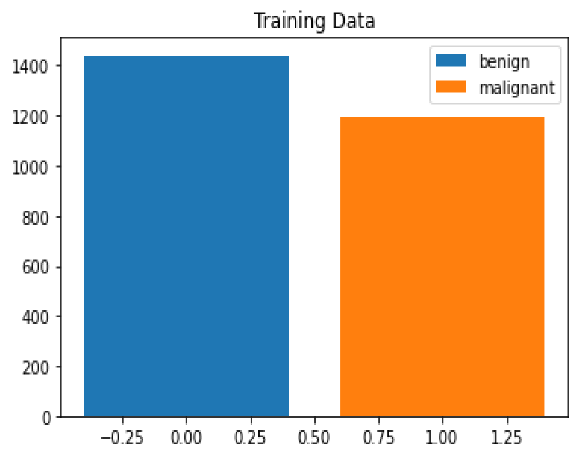

Figure 5: The training data exhibits both benign and malignant data.

The figure 5 shows "Training Data," comparing the number of benign and malignant cases used for training in a machine learning model. The blue bar represents benign cases and the orange bar represents malignant cases, with both bars being of similar height. This suggests that the dataset includes a comparable number of examples for both classes, which is beneficial for model training as it helps prevent bias towards one class. This balance allows the model to learn to distinguish between benign and malignant lesions with a reduced risk of overfitting to the most frequent label.

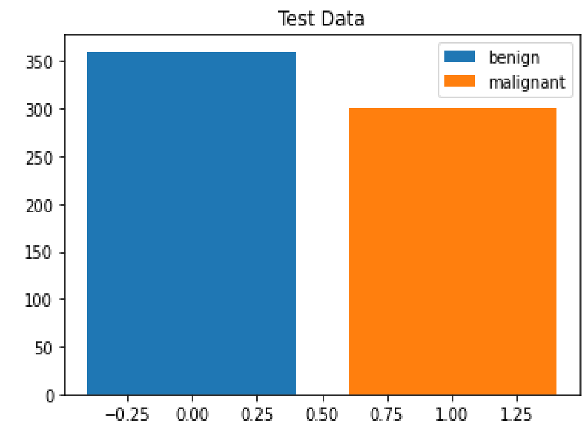

Figure 6: The data shown during the test includes both benign and cancerous samples.

The figure 6 depicts "Test Data" which shows the distribution of benign and malignant cases within a test dataset, presumably for a machine learning model focused on medical diagnostics. Both the benign (blue bar) and malignant (orange bar) cases are represented in nearly equal amounts, which is a common practice to ensure that the model's performance is evaluated on a balanced dataset. This balance helps in assessing the true predictive power of the model across different classes and ensures that its accuracy is not skewed by an uneven distribution of test cases.

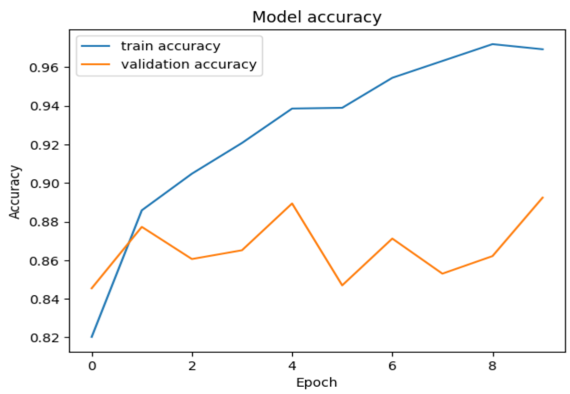

Figure 7: Demonstrates the correctness of the model.

The figure 7 presents "Model accuracy," showing the progression of training accuracy and validation accuracy over a series of epochs during the training of a machine learning model. The blue line represents the training accuracy, and it demonstrates a steady increase, suggesting that the model is effectively learning from the training data. The orange line represents the validation accuracy, which exhibits some fluctuations but generally trends upwards. This indicates that while the model is learning, there may be some overfitting or instability in how the model generalizes to new, unseen data. The goal in such training is to have both lines as high as possible and close together, which would suggest good performance and generalizability of the model.

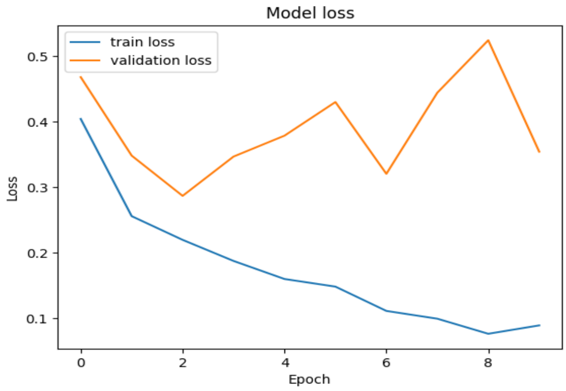

Figure 8: Shows model loss.

The figure 8 shows the "Model loss," depicting the train loss and validation loss over a number of epochs during the training of a machine learning model. The blue line, which represents train loss, shows a consistent decline, suggesting that the model is improving and learning from the training data as the epochs progress. In contrast, the orange line representing validation loss decreases initially but then fluctuates and increases, indicating potential issues such as overfitting to the training data or a lack of generalization to the validation data. The ideal outcome would be for both lines to decrease and converge, indicating that the model is not only fitting the training data well but also generalizing well to new, unseen data.

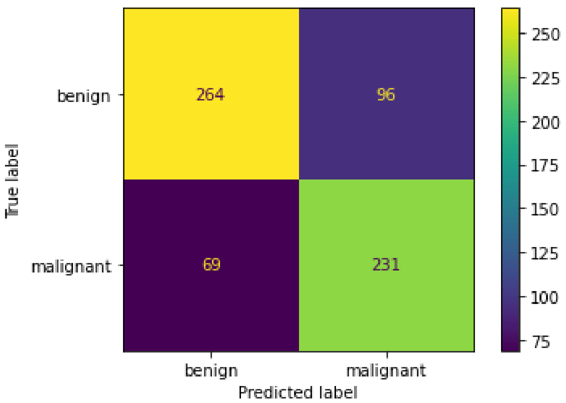

Figure 9: Shows confusion matrix of proposed work.

The figure 9 illustrates a confusion matrix for a classification model predicting benign and malignant cases. The matrix shows four quadrants: true positives (benign cases correctly predicted as benign) with a count of 264, false negatives (malignant cases incorrectly predicted as benign) with a count of 69, true negatives (malignant cases correctly predicted as malignant) with a count of 231, and false positives (benign cases incorrectly predicted as malignant) with a count of 96. The counts indicate that while the model is relatively accurate, there are instances of both false positives and false negatives, which are critical in the medical diagnosis context as they represent potential diagnostic errors. The goal in medical diagnostics is to minimize false negatives and false positives to ensure accurate and reliable detection of malignant cases.

4.1 Comparative result existing and proposed method

Table 2 Comparative result existing and proposed method.

S. No.	Methods	Accuracy (%)	Precision (%)	recall (%)	Loss
1.	KNN	86	88	87	0.9147
2.	ANN	89	90	91	0.8523
3.	GAN	90	93	95	0.5685
4.	CNN	96	97	96	0.0893

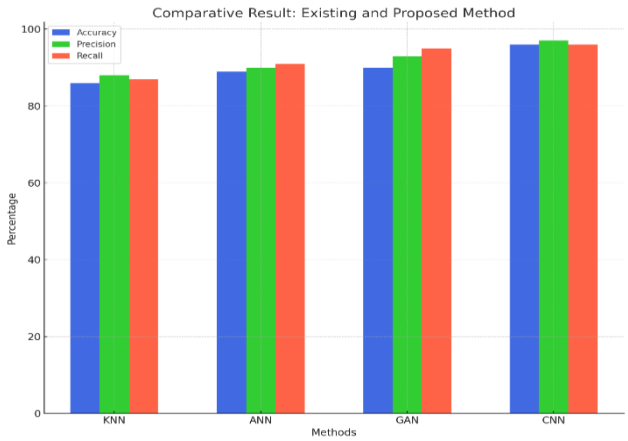

Figure 10. Comparative result existing and proposed method

The image displays a bar chart titled "Comparative Result: Existing and Proposed Method," comparing the performance metrics of accuracy, precision, and recall for four different machine learning methods: KNN (K-Nearest Neighbors), ANN (Artificial Neural Network), GAN (Generative Adversarial Network), and CNN (Convolutional Neural Network). Each method has three bars representing the mentioned metrics. The chart is designed to compare how each method performs in terms of these metrics, likely in the context of classification tasks. All methods show high percentages across the metrics, suggesting they are all reasonably effective, with small variations in performance between them. The comparative analysis helps in selecting the most appropriate algorithm for a specific task based on the desired balance of accuracy, precision, and recall.

5. Conclusion

An advanced automated diagnostic tool was developed using sophisticated digital image processing methods to accurately classify various skin ailments. The cornerstone of this system is a convolutional neural network (CNN), meticulously architected with three distinct hidden layers. These layers are methodically designed, each containing a 3x3 filter matrix that systematically amplifies the number of output channels, beginning with 16, escalating to 32, and culminating at 64. The architecture is further augmented by a densely connected layer, which is seamlessly integrated to facilitate complex pattern recognition.

The CNN's predictive capacity is harnessed using a softmax function, which enables the categorization of inputs into probabilistic outputs across multiple classes. In handling the 64 input channels, the model takes advantage of this activation function to make nuanced distinctions between different types of skin conditions.

To refine the model's predictive prowess, an AdamW optimizer was employed. This optimizer is a modification of the standard Adam optimization algorithm, offering an adjustment for each parameter's decay rate to improve convergence. By leveraging the strengths of AdamW, the system has been finely tuned to minimize error rates.

The effectiveness of combining a meticulously designed CNN with the AdamW optimization technique is evidenced in the impressive diagnostic results. The system has achieved a notable accuracy rate of 96%, signifying its reliability in medical assessments. Furthermore, the optimization has resulted in a remarkably low loss rate of 0.0893, indicating the model's efficiency in learning from the data and its potential for use in clinical settings to support and enhance decision-making processes.

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Conflicts of interest

The authors declare no conflicts of interest.

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