Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

A Deep Learning Framework for Accurate Skin Disease Diagnosis Using CNNs

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- Received Date: 08 Jan 2026
- Accepted Date: 25 Jan 2026
- Publication Date: 15 Mar 2026

Keywords

Skin disease diagnosis, convolutional neural networks, transfer learning, ResNet50, DenseNet201, medical image classification

Abstract

The proposed project is an automated skin disease diagnosis framework based on deep learning consisting of convolutional neural networks implemented in a web-based application. The system will have two different diagnostic functions, which include the classification of the skin disease and identifying the type of skin cancer. The framework applies the transfer learning based on the pretrained convolutional neural network models, with a ResNet50-based model applied to general skin disease and DenseNet201-based model applied to skin cancer. Both models accept the dermal images resized to 224 x 224 pixels and then they do multiclass classification with the help of the softmax activation. The training plan involves extraction of features and refinement of the deeper layers to promote the domain-specific learning of features. Regularization methods like dropout and batch normalization are also added in order to enhance generalization and minimize overfitting. The trained models are deployed in a system that is built on Flask, which allows authentication of the users, uploading of images and real time inference. The prediction consists of class label predictions and confidence scores and class probability distributions. The dual-model architecture enables the system to respond to the different degrees of diagnostic complexity and at the same time be computationally efficient. The framework offers an organized system of applying deep learning models to practical healthcare assistance systems that will allow the opportunity to conduct the initial screening of skin conditions in an accessible and automatic manner.

Introduction

Skin diseases are one of the most widespread types of medical disorders that occur in people of different ages and nationalities. The conditions may be mild and not life threatening like acnes and eczema; severe and fatal like melanoma and other skin cancer. The firsthand identification and proper diagnosis is very important in proper treatment and prevention of disease development. Nevertheless, the conventional diagnostic procedures are mostly dependent on the visual inspection by the dermatologists which is subjective, time-consuming and constrained by the presence of the specialized medical practitioners. In most areas, particularly where resources are limited, dermatological skills are low and patients are thus diagnosed late and thus treated poorly. This results in a high demand of automated, dependable, and convenient diagnostic systems that can help in detecting the skin conditions at an early stage.

The new opportunities of medical image analysis have become possible due to recent achievements in artificial intelligence and deep learning. Convolutional neural networks have been largely successful in activities that relate to image classification, object detection, as well as pattern recognition. These models can automatically derive hierarchical features of the images hence they are very applicable in the analysis of intricate visual patterns in images of the dermis. Within the framework of dermatology, convolutional neural networks can be trained to detect minor changes in the skin texture, color, and lesion structure and thus distinguish between different skin diseases with a high level of accuracy. Transfer learning is an additional product of this ability as it utilizes the pretrained models which have already mastered the general image properties on large-scale scales and thus do not require large amounts of domain-specific data and calculations.

The project introduces a deep learning-based system of proper skin disease diagnosis by the use of convolutional neural networks as a part of a web-based application. The system is coded to have a two-model architecture to deal with two issues of diagnosis, which are not the same yet closely related. The former one is dedicated to the identification of typical skin diseases with the help of a ResNet50-based model. The model is firstly trained with

Citation: Kiran Kumar M, Sri Venkata Narayana T , Yaswi Satya Akshith T, Srivatsan R. A Deep Learning Framework for Accurate Skin Disease Diagnosis Using CNNs. GJEIIR. 2026;6(3):221.

the feature extraction, and the pretrained layers are frozen so that they can be used in the form of learned representations and then the deep layers are fine-tuned to fit the domain features of the skin images. The second one is aimed at classifying and identifying types of skin cancer with the help of a model based on DenseNet201. DenseNet networks are characterized by efficient feature reuse, and good gradient flow, thus are well adapted to fine-grained and complicated classification tasks (e.g. lesion recognition). The division of these two tasks in special models guarantees the system an improved specialization and better results of the diagnostic.

The framework works on preprocessed and resized dermal images of a uniform input dimension that is appropriate to the convolutional neural networks. During the training process, data augmentation methods are used to increase the robustness of the model and also to enhance the generalization by simulating the changes in the orientation, scale and lighting conditions. The model architectures also include regularization techniques like dropout and batch normalization to ensure that the training process is not overfitted or to stabilize it. The optimization algorithms to train the models are adaptive in terms of varying learning rates among themselves, and hence, effective convergence is guaranteed. The end result of both models is a probability distribution of predefined classes, which is gained by use of softmax activation, and this enables the system to give not only the label that is predicted, but also a form of confidence of the prediction.

Besides the deep learning basics, the project will be used to incorporate a web-based interface that is created with a lightweight application framework. This interface allows one to add pictures, choose the kind of diagnosis, and get the results in real time. The system has user authentication systems to make sure that there is a secure access and custom interaction. When an image is submitted, the correct model is called on the basis of the chosen diagnostic mode and the result obtained is analyzed and presented in an organized form showing the predicted classes and the confidence scores attached to them. This helps in narrowing down the gap between the complex machine learning models and the end users, making the system viable and accessible to the end users.

The reason to work on this is the necessity to offer an efficient and scalable solution to the preliminary screening of skin diseases. Although the system is not supposed to substitute the professional medical diagnosis, it can be used as a support means that may help the user to recognize possible conditions and seek medical help in time. Deep learning models allow the analysis to be consistent and repeatable, which is not as consistent as the analysis when analyzing using a human eye. Moreover, the framework has a modular nature, which can be advanced in the future, e.g. by adding more disease categories, better datasets and more advanced models with more modules.

In general, the given project shows how convolutional neural networks can be used in solving real-life healthcare solutions. The system has a combination of transfer learning, dual-model architecture, and web-based deployment to give a complete solution to automated skin disease diagnosis. The strategy accentuates the power of artificial intelligence to enhance the approach to accessibility and efficiency in medical diagnostics in such spheres where professional consultation could not be easily offered.

Literature Survey

During the recent years, the use of deep learning methods in the field of skin disease classification has attracted a lot of attention because of its capability to automatically identify more complex features of the medical images. Rangaswamy et al. [1] investigated the application of convolutional neural networks to classify skin diseases and proved that the deep learning models could be successfully used to outperform other image processing and machine learning algorithms. The relevance of hierarchy in extracting features in their work is based on the fact that it is more effective in capturing variations in skin texture and lesion patterns. Equally, Alruwaili and Mohamed [2] suggested a combined deep learning model that used EfficientNet and ResNet models. This mixed method takes advantage of the benefits of both networks and allows to represent features better and increase the classification accuracy in the case of multiclass skin diseases.

Transformer-based architectures have also been brought to the field of medical image analysis with the development of deep learning. The article by Mohan et al. [3] explored the application of transformer based models with explainable artificial intelligence to classify skin diseases. They point out that long-range dependencies of image features are captured by the transformer that result in a better classification performance. Moreover, explainability techniques are integrated, and this makes model prediction transparent, which is important in healthcare applications. A different research conducted by Aquil et al. [4] dealt with the issue of detecting skin diseases under a variety of tones. Their composite machine learning and deep learning style makes them better at generalization and fair predictions, which is a major drawback of previous models, which was usually biased towards a particular dataset.

Ensemble and multi-model architecture have also been used to improve the performance of classification. The researchers of Badr et al. [5] created a multi-model deep learning architecture used in diagnosing multi-class skin diseases and showed that by combining a set of multiple models, they could capture features that are complementary to each other and enhance robustness of the system. Anand et al. [6] proposed an augmented hybrid framework with GAN to increase the diversity of the dataset. GAN-based data augmentation can assist in solving the problem of data scarcity and imbalance, which is typical in medical imaging. Besides, the fact that they have included explainable AI models like LIME or SHAP can give information about how the model made specific choices, which makes the system more reliable and trustworthy.

The comparison of various deep learning architectures has been a very useful experience in the selection of the model and trade-offs in performance. Shams et al. [7] have made a comparative analysis of ResNet50, MobileNet, and EfficientNet-B0 on skin disease classification. Their results suggest that although deeper networks like ResNet50 are more accurate because they can learn more complicated representations, lightweight networks like MobileNet are faster to infer and have lower computational needs and could be applied in the real-time. The model suggested by Liu et al. [8] includes the multi-scale feature extraction and effective channel attention algorithms. This method improves the capacity of the model to concentrate on the parts of the image which are of interest hence the high rate of classification as it captures both the global and local features.

The most recent studies have also been dedicated to the practical issues of deployment like data privacy and scalability. Alasbali et al. [9] proposed a privacy-aware skin disease classification system, based on federated learning, on an IoT-based edge computing system. Their method will enable them to train models on decentralized data sources without sensitive patient data exchange, which is a guarantee of privacy, but does not affect performance. This is more so in cases of application in the healthcare where data confidentiality is paramount. Moreover, Liu et al. [10] came up with FUSCANet in which they integrate feature fusion and spatial-channel attention to improve the classification. Their model illustrates the success of the combination of several patterns of feature extraction to represent complicated trends on skin images.

On the whole, it can be concluded that the literature shows a clear path of the development of traditional convolutional neural network models to more sophisticated ones with hybrid models, attention mechanisms, and transformer-based models. The combination of explainable AI features and privacy-saving models is another factor that increases the relevance of the systems in the real-life healthcare environment. Irrespective of these developments, issues like the imbalance of data, availability of different types of data and the necessity of strong generalization of various populations are still a problematic aspect. The studies reviewed also point out the relevance of the combination of sophisticated architectures with such practical principles as interpretability and privacy. The proposed project is based on these already existing works, which involves the use of transfer learning-based convolutional neural networks and dual-model architecture to solve general skin disease classification and skin cancer detection, and thus, to help in the creation of effective and scalable diagnostic systems.

Proposed Methodology

The suggested system will introduce a deep learning-based architecture of automation of skin diseases detection with the help of convolutional neural networks embedded in a web-based application. The methodology will be used to conduct precise classification of dermal images with the use of a dual-model architecture, with each model dedicated to a certain diagnostic task. The architecture is structured in a pipeline that entails preprocessing of the data, creating the model, training, assessing, and implementing it by using real-time inferences.

Data acquisition and Preprocessing.

The system uses the image datasets of dermal images of various types of skin diseases and skin cancer conditions. The images are gathered and sorted into fixed categories in accordance to diagnostic names. In order to maintain consistency in model input, all images are rescaled to a standard size of 224 x 224 pixels having three color channels. Preprocessing steps involve normalization of pixel values and scaling of pixel values to ensure that the values are numerical and that they are not affected by extreme values. The manipulation of data to augment diversity of the dataset and enhance model generalization includes data rotation, flipping, zooming and shifting. These changes contribute towards the simulation of real world changes in image orientation and changes in lighting conditions so that the model may learn robust feature representations.

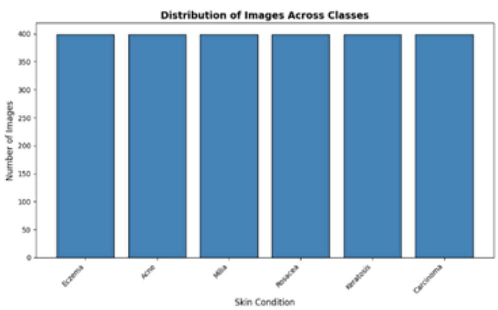
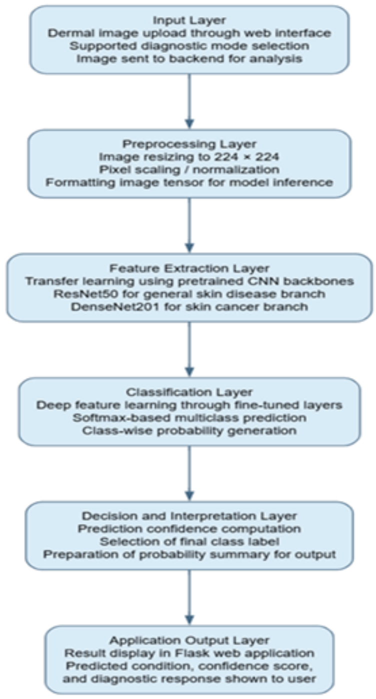


***Figure 1**. Distribution of skin disease images across different classes*

Design Arch. of Model Architecture.

The framework uses two convolutional neural network architectures, which are founded on the transfer learning. The former is based on a pretrained ResNet50 to conduct general skin disease classification. The choice of this model is motivated by the fact that it is able to reflect extensive hierarchical aspects with the aid of residual connections that overcome vanishing gradient problems. The second model is based on classifying skin cancers with the use of DenseNet201, which has a dense pattern of connectivity, which guarantees the effective reuse of features and the enhancement of gradient flow. Both models are pretrained and are further extended to any custom classification layer such as global average pooling, fully connected layer and softmax activation to predict multiclasses. This two-model structure enables the system to be able to process varying amounts of diagnostic complexity.



Training Plan and Refinement.

The training is done in two phases namely, feature extraction and fine-tuning. This involves training the pretrained backbone layers at the first stage whereafter only the custom classification layers are trained. This allows the model to use acquired generic image characteristics and also adjust to the particular skin disease dataset. During the fine-tuning phase, some additional layers of the already trained networks are unfrozen and the model is left to optimize the representation of features that are particular to the dermal image patterns. Adaptive algorithms are utilized to perform optimization, and early stopping and learning rate scheduling are some of the methods used to avoid overfitting and achieve effective convergence. This is with regularization techniques such as dropout and batch normalization which are added to enhance generalization.

Mechanism of Classification and Prediction.

The trained models do the multiclass classification by use of softmax activation in the output layer. In a given input image, the model provides a probability distribution of all the possible classes. The probability of the highest class is taken to be the predicted label. Besides the expected class, the system will give confidence scores and probability per class as a measure of offering a more detailed insight into the prediction. The dual-model methodology will be used to ensure that the right model is used depending on the diagnostic need, which is the general skin disease or skin cancer. The separation increases accuracy and minimizes model ambiguity.

System Integration and Deployment.

The deep learning models are embedded into a web based application through the lightweight server framework. The system has the user authentication option to control the secure access. The interface can be used to upload dermal images and choose the type of diagnosis needed by a user. The backend takes the image and forwards to the correct model at which the image is inferred. The real-time display of the prediction outcomes is then provided on the user interface. The deployment architecture will make sure that there is an effective communication between the frontend and backend components of the architecture, which will allow a seamless interaction and prompt response times.

Performance Evaluation and Interpretation of the output.

The standard classification measures used to assess the performance of the models include accuracy, precision, recall and F1-score. These measures give an idea of how the model is capable of classifying various types of skin conditions in the right manner. The confusion matrix analysis helps to determine the misclassification trends as well as determine model reliability between classes. The system also produces the predicted class but also the probabilities related to the class hence the user can understand the results. The system of the structured output format makes the process of its use more convenient and promotes the making of informed decisions. The methodology will provide the system with the ability to be scaled and modified in the future to be improved through adding more datasets or sophisticated architectures.

Implementation and Results

The suggested framework of skin disease diagnosis is implemented through the combination of the deep learning models with the web-based application to allow real-time prediction and interaction with the user. The system is structured in the form of a pipeline that is modular with the data processing, model training, model integration, and deployment. The implementation of the models is to make sure that both the skin disease classification model and the skin cancer classification model work efficiently in a coherent system and their respective specialization is observed.

Environment and Tools of Implementation.

The system is executed with the help of Python as the main programming language with the TensorFlow and Keras frameworks to create and train the convolutional neural network models. The web application is developed on a lightweight server-side framework, which allows the intensive interaction between the frontend and the backend parts. An interactive user interface in terms of uploading the image and visualization of the results is created with the help of HTML templates and styling frameworks. The SQLite is employed in the management of user authentication information. The trained models are stored in the form of serialize and loaded into the application at the time of the execution to do the inference. The implementation makes sure that it is compatible with standard computing environments and can be efficiently run without having a high-end hardware when making an inference.

Model Integration and Workflow.

The trained models are added to the application backend to accomplish prediction. The procedure starts when a user has uploaded an image and has chosen the mode that he wants to be diagnosed with. According to the selecting, the system directs the input image to the relevant model. The image is preprocessed in the form of resizing to 224 X 224 pixels and normalization to the model specifications. Predictions are then generated using the processed image, which is then run through the convolutional neural network selected. The result is a probability distribution over fixed classes, based on which the resulting prediction label is obtained. The system makes sure that the preprocessing pipeline applied during the inference is the same as the one applied during training so that it can be trusted in making predictions.

User Interface/Interaction.

The user interface is made to have a user-friendly and easy to use interface. It also has user registration and user log in features which provides a secure system access. After the authentication, users are directed to the detection interface, where they have the ability of uploading dermal images and choosing the diagnostic category. The interface shows the results of the uploaded image and the prediction results. These are the predicted class, confidence score and a probability distribution across all the classes. The presented model is structured in such a way that users can interpret the model output. The interface is made as simple as possible but at the same time making it clear and accessible.

Training Intervention and Model Behavior.

It is through transfer learning techniques that the models are trained. The model based on ResNet50 is trained to classify general skin diseases whereas the one based on DenseNet201 is trained to detect skin cancer. Training is performed in two phases, the first phase is the freezing of pre trained layers and the second phase is the fine tuning where the desired deeper layers are unfrozen. Training Data augmentation is used to enhance generalization and manage changes in image conditions. To avoid overfitting, regularization methods of dropout and batch normalization are used. The adaptive optimization algorithms are used to train the models and validation metrics are used to monitor progress of training. The best performance in terms of validation is used to save model checkpoints.

Results and Performance Analysis.

The effectiveness of the applied models is measured based on conventional classification measures obtained out of the training and testing of both models. The skin disease classification model has a high level of performance, as the accuracy is high and the precision and recall are balanced in most of the classes. The model is effective in separating various skin conditions, which means that the process of extracting features as well as fine-tuning has managed to capture patterns of the dermal images that were relevant. The confusion analysis has indicated that the vast majority of the classes are properly classified, and there are only significant overlaps between visually similar conditions.

On the contrary, the skin cancer classification model has moderate performance in comparison to the general disease model. The accuracy of classification is lower to be explained by the complication of lesion patterns and unequal distribution of classes in the dataset. Some classes that possess smaller samples of training demonstrate lower recall meaning that the model is not able to generalize under-represented categories. In spite of this weakness, the model can also produce significant classes with a decent amount of accuracy, and this shows that it can be used in preliminary screening.

The models give more information on the level of prediction confidence due to the probability-based output. Where the model has a high degree of confidence, the probability of the prediction is far much greater than the rest, meaning that there is clear separation of features. The probability distribution in a case of ambiguity is more diffused, that is, there is uncertainty in the classification. This action shows that giving probability scores and the labels which are predicted are important in aid of informed interpretation.

System Evaluation and Observations.

The hybrid system provides evidence of the feasibility of the deep learning in the field of dermatological diagnosis. Prediction response time is effective, and it can be used to interact in real-time without delays. The modular design can be easily scaled and can be improved later, e.g. by adding more disease classes or by better architectures. The specialization of the diagnosis tasks into two models enhances the reduction of misclassification between general skin diseases and cancerous lesions.

Nevertheless, some weaknesses are witnessed in the implementation. The imbalance in the datasets influences the performance of the skin cancer model, as it affects the model in terms of the capability to effectively classify the rare conditions. Moreover, the system is dependent on the quality of the image and changes in the lighting or resolution may alter the results of predictions. The factors indicate the necessity of expansion of the datasets and the improvement of the preprocessing.

All in all, the implementation is successful as it proves the existence of a practical and effective deep learning-based diagnostic system. The findings suggest that the convolutional neural networks along with transfer learning and system integration can be used to offer reliable support to automated skin disease classification. The framework can be used as a basis to continue research and development in the field of AI-assisted healthcare applications, and probably enhance the accessibility and early diagnosis of skin conditions.

Conclusion

The given work illustrates how to design and implement a deep learning-based structure of automated skin disease diagnosis with the help of convolutional neural networks that are implemented in a web-based application. The system is designed with a dual-model framework that solves two different diagnostic problems which include the general skin disease classification and the skin cancer detection. The framework makes use of transfer learning using fixed convolutional neural network structures and thus, is able to make use of existing representations of features and adapt them to domain specific dermal image analysis. The application of the ResNet50 to general skin disease classification and DenseNet201 to skin cancer detection is a conscious design decision that is set to strike the right balance between the ability to perform computations with the capacity to extract precise and specific features. The preprocessing techniques, data augmentation, and regularization strategies are integrated to the methodology so that generalization and robustness of the model are enhanced so that the system can be used to deal with variations on the input images.

The application of the framework into a web-based system further increases its practical usefulness as it allows the interaction of the user by uploading images, real-time prediction, and structured visualization of the results. The combination of the deep learning models in the background with the user-friendly interface makes the system accessible and easy to operate even with the persons that lack technical knowledge. The results of the system are the predicted class labels, the scores on the level of confidence, and the probability distributions per class which, in combination, will provide a detailed insight into the decision-making process of the model. This is not only better than making the results more user friendly but also aids in making informed interpretation of the results. System modularity enables the structure to be scaled and flexible, which means that one can in the future add to the structure new disease categories, better datasets, or more complicated model structures.

The outcomes of the models adopted reveal the fact that deep learning methods are very effective to perform tasks related to the classification of skin diseases. The ResNet50-based model has good results in the detection of common skin conditions, as it uses hierarchical image features, and it uses the fine-tuning strategy. Although more sophisticated, the DenseNet201-based model deals with the issues related to the classification of skin cancer because it makes use of dense connectivity and increased feature propagation. Its performance is relatively average because of the complexity of the lesion patterns and the imbalance of the datasets, but it still can give significant predictions that can be used to give preliminary screening. The effectiveness of the proposed approach is also proven by the evaluation of the model performance based on the standard measures, namely the accuracy, precision, recall, and F1-score, whereas the analysis of the confusion matrix helps to understand the behavior of the classification and the ways to improve it.

The framework emphasizes the need to separate the diagnostic tasks into specialized models in order to enhance the accuracy and decrease ambiguity. The system separates the general skin diseases and the cancer specific conditions which eliminates the constraints that come with one unified model which tries to deal with varied classification needs. This design choice is part of enhanced performance and it is in line with the practicality of the dermatological diagnosis which necessitates different degrees of analysis in the various types of conditions. Moreover, the fact that the probability-based outputs can be used increases the transparency as it gives the confidence levels that the users can comprehend the level of confidence they have on each prediction.

In spite of these advantages, the system has a number of limitations that should be considered, as well. Imbalance in the dataset affects the performance of the skin cancer classification model as it impacts on the model in detecting the underrepresented classes with the required accuracy. Also, the system depends on the quality of images, so in case of light changes, and resolution alterations, or differences in image capturing conditions, the accuracy of prediction may be affected. The challenges have led to the need to make more improvements including increasing the amount of data, using more sophisticated data balancing techniques, and using more powerful means to perform preprocessing. In addition, the system is not meant to substitute professional medical diagnosis although it does give automated predictions. Rather, it is an aid to pre-screening and awareness of the need to consult healthcare professionals in order to make a final diagnosis and treatment.

To sum up, the suggested framework has been effective in illustrating the use of convolutional neural networks in the diagnosis of skin diseases automatically. The system integrates transfer learning, dual-model architecture, and web-based deployment, which offers an overall and viable method of dermal image analysis. The gap between the sophisticated techniques of computations and the practical use of deep learning models and a convenient interface is closed. The project highlights the opportunities of artificial intelligence to improve the efficiency of diagnostics, accessibility, and early detection of skin diseases. As improved and extended, the framework can be used to achieve more sophisticated and trustworthy AI-assisted medical systems, which in the end will aid in enhancing healthcare results.

Result

The proposed deep learning framework that is used to evaluate the performance of the skin disease diagnosis is founded on the behaviour of the trained convolutional neural network models incorporated into the system. The findings indicate the quality of the dual-model design, in which the classification of general skin diseases and skin cancer are done by different models. The testing takes into account the classification ability, consistency of prediction, and the system behavior in general when conducting inference. The models produce probability outputs in relation to each input image, and it can be used to predict labels and estimate confidence that is essential in determining the reliability of the system.

The classification model of skin disease based on a pretrained ResNet50 architecture that has been fine-tuned has shown a high ability to distinguish various types of frequent skin diseases. The model is very effective in visual patterns like changes in texture, color distributions, and structures of lesions found in dermal images. In the process of evaluation, the predictions reveal that there is a distinct separation of the classes with large values of confidences of samples that are correctly classified. The probability distributions of the softmax layer show that in most instances, the model gives much greater probabilities to the correct class, which shows feature representations learned well. The classification behavior indicates that the fine-tuning and feature extraction process has managed to change the pretrained network to the domain of the skin disease analysis. The model has an equal level of performance in various classes and there is a low degree of confusion of visually distinct conditions which implies a high level of generalization.

The patterns of confusion which are witnessed in the classification result indicate that misclassification is mainly between classes which have similar visual attributes. As an illustration, some inflammatory disorders can present similarities, and therefore, they can be unpredictable sometimes. These examples, however, are quite few, and the general trend of classification is the same. The model is also stable in predicting using dissimilar input samples, and it is reliable in real-time inference operations. This robustness is also achieved through the use of data augmentation during training whereby the model is able to accommodate change in image rotation, size, and brightness. Consequently, the system is effective in situations where the input images have a slight distortion or inconsistencies.

Figure 2. *Sample classification results with predictions and confidence scores*

On the contrary, the skin cancer classification model, which is built on DenseNet201, demonstrates moderate results because of the complexity of lesion classification and data imbalance. The model can recognize major lesion categories with a reasonable accuracy, although its results in different classes are not consistent. Classes that have more training samples are more accurate in their predictions and the classes that are underrepresented have low recall and high misclassification rates. This action suggests that the learning process of the model depends on the distribution of the training data and it is important to have balanced datasets in order to classify medical images. The probability distribution of the cancer model is more spread than the disease model which reflects higher uncertainty in category especially in cases that are difficult to classify.

These restrictions notwithstanding, DenseNet201 model is capable of extracting complicated patterns in the images of skin lesions. Dense connectivity that is used enables the model to share features across layers and enhance its ability to learn fine-grained features. The dropout and batch normalization are also supported by inclusion of multiple fully connected layers, which further increases the ability of the model to generalize, but due to the availability of data, its effectiveness is limited. The findings propose that the model can be used in initial screening, but additional enhancement on the size and balance of the dataset is necessary to attain higher reliability in the use of the model in critical diagnostic applications.

The integrated system integrates the results of both models in a single interface to ensure that the users have a smooth diagnostic process. The prediction outcome is in a well-organized format comprising of the identified class, confidence score and probability distribution of the classes. Such form will enable the users to understand the results better, since it will give them an idea on the certainty of the model and possible alternative classification. The system is efficient in terms of response time as real time interaction is possible without much delays. The backend processing is used to ensure that the correct model is chosen depending on the input of a user in a consistent manner in the way the prediction is made.

Preprocessing consistency is also important as observed during the evaluation of the system. The models have certain preprocesses like the ability to resize and normalize images to correspond to the conditions in which they have been trained. The implementation will make sure that the following steps are used in an appropriate way during inference and that the integrity of the predictions is kept. Anything that varies during the preprocessing may influence the model performance, and thus one should be keen on aligning the training and deployment pipelines. This consistency has been achieved through the system, which adds to the stable and reliable results.

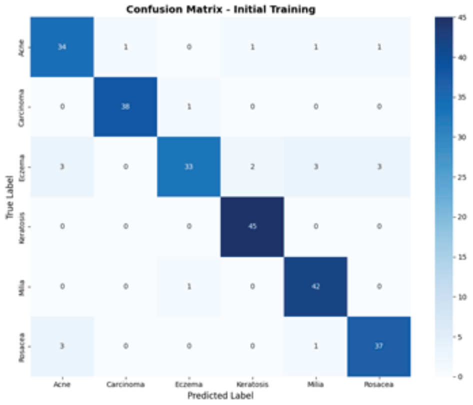


Figure.3:*Confusion matrix showing classification performance of the model*

The other significant finding made on the results is the use of probability-based outputs in uncertainty management. When the model is certain, the probability of the predicted class is very high as compared to others hence giving clear and decisive outcomes. Where the model is not known, the probability distribution is more homogenous, which means that there is ambiguity in classification. This action will help in pointing out the cases that can need additional expertise assessment. The system makes predictions and probability scores more transparent and can be used in making better decisions.

Altogether, the findings show that the suggested framework is able to make use of deep learning models to diagnose skin diseases automatically. The model based on ResNet50 has a high classification performance with general skin diseases whereas the DenseNet201 model has a practical use of skin cancer detection, regardless of the difficulties encountered due to imbalance in the data. The dual-model structure enhances specialization and minimizes ambiguity in classification, which is one of the factors that bring about performance of the system. The fact that these models are integrated into a web-based application is yet another confirmation of the practical situability of the framework as it facilitates the availability of diagnostic support in real time. The results have shown that with the help of the transfer learning and the correct design of the system, convolutional neural networks can become a solid basis of the creation of AI-assisted health care solutions

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