MSc in Artificial Intelligence and Data Science

771764_A21_T3A: MSc Research Project

Student: Venu Madhuri Yerramsetti - 202124284

Supervisor: Dr. Oseikhuemen Davis O Ojie

Skin related issues diagnosis using image analysis

Abstract

Human skin provides coverage to muscles, bones, and all other body parts, making it one of the largest organs in the body. When there is an abnormality in skin function, other organs may be affected, thus the importance of skin functions should not be underestimated. In terms of global burden, most people suffer from skin diseases at some point in their lives. Patients with chronic and incurable skin diseases, such as psoriasis and eczema, often experience significant morbidities, such as physical pain and reduced quality of life.

As part of this study, we will train a convolution neural network model by collecting images of skin lesions of five skin diseases, chronic wounds to predict their presence. An image of the infected area of skin will be provided as an input to the website by the patient., This image is subjected to deep learning techniques and, as a result, the website will be able to detect skin problems from the defined set of ailments trained and suggests tips and treatments after detecting the issue. For future advancements, the system can be trained to detect multiple diseases. Alternatively, we will evaluate available variety of machine learning algorithms today, including Naive Bayes, Decision trees, Random Forests, and support vector machines to assess how better they perform and conclude why we choose deep learning techniques and propose a model for skin disease detection. Over model has achieved an accuracy of 73.18 per cent validation accuracy using convolution neural networks.

1. Introductions and Background

As a medical science, dermatology, [1] as a discipline focuses on diagnosing and treating diseases related to the skin, hair, and nails, as well as assessing chronic wounds. Clinician appointments with dermatologists and wound care specialists are often expensive, take a great deal of time, and do not usually qualify for insurance coverage.

Skin is more susceptible to disease and infection due to its close relationship to the outside environment. Combat skin diseases, we need to pay more attention to them. Chronic wounds tend to be associated with the vascular system, whereas skin diseases [2] are most caused by bacteria, fungi, viral infections, environmental factors, or geographical situations. A variety of disorders can result in these conditions, ranging from the easily self-treatable to the potentially fatal like skin cancer to the difficult to treat such as venous leg ulcers and pressure ulcers. Therefore, it is crucial to obtain a proper diagnosis. Lesion areas are places on the skin where there is infection. In most cases, skin lesions are the first sign of an underlying disease. It is due to the essence of computer vision methodology that it has drawn researchers worldwide due to its ability to equip efficient information for adequate illustrated and practical study in modern life. Image classification is another promising approach in computer vision, which is used in various applications including pattern recognition, remote sensing applications, medical imaging, etc.

1.1 Literature Reviews

We will take inspiration from these papers and incorporate some of the methods into the project to determine what type of skin disorder is present with the images. Several studies have been made to predict the type of skin disease employing image processing. Some of these approaches have been more accurate than others for the breakdowns.

- Using colour image processing, colour gradients, and k-means clustering techniques in Dermatology, Arifin et al [3] provided a paper in which a method has been presented for automatic detection of skin anomalies and diseases on a total of six images. The system performed 95.99% in identifying diseased skin, and 95.016% in identifying the disease. It will be similar in some respects to this algorithm, but we will be targeting five types of common skin diseases, and the number of images we will be using will be greater as opposed to this study.
- It has been proposed by Sumithra et al [4], to segment and classify skin lesions by removing hair and noise from images and extracting lesion areas based on colour and texture features of the images. k-nearest neighbors (K-NNs) and support vector machines (SVMs) are the two classification algorithms used in this application to classify the images based on their features. Based on the results performed with SVM and K-NN classifiers alone, and then with fusion, respectively, the system obtained F-measures of 46.71%, 34% and 61%. Similarly, we have tried machine learning algorithms for training but also adapted neural networks.
- Harangi, B. et al [5], used an ensemble of different neural networks to achieve classification accuracy by combining the best performing CNNs. This review study suggests a rugged combination of uniform distribution-based segmentation and active contouring, with a maximum system accuracy of 97%. Furthermore, Discrete Wavelength Transform (DWT's) using the Principal Component Analysis (PCA) method results in an accuracy of approximately 98%, which is higher than that of any other feature extraction method. Furthermore, the SVM with k-NN method has a higher accuracy of around 98% than other methods for classification. By selecting different methods for the author for fusion, we will also apply a similar technique to the study to achieve the maximum level of accuracy**.**

2. Methodology

2.1 Data Collection:

In the training process of a model, collecting data is an influential step. A contractual agreement has been drawn up with Simon Hudson (Licensor) from Novia Works, whose resource contains approximately 15,000 wound and skin lesion images in image and database format. In this study, we have used 1229, 8494, and 2520 images of diabetic, pressure ulcer, and venomous ulcer images, respectively. Additionally, the data is also available on the Kaggle website [6], which contains data for ten types of skin diseases, among which we have chosen two folders of images those for psoriasis and eczema containing 2055 images and 1677 images, respectively.

Figure 1: Visualisation of the image dataset, copyrights provided on contractual agreement basis by Simon Hudson for project purpose.

2.1.1 Explanation of Categories in the data:

Category	Disease	Number of Images	Source
0	Diabetic	1229	Simon Hudson
1	Pressure Ulcer (PU)	8494	Simon Hudson
2	Venomous Ulcer (VLU)	2520	Simon Hudson
3	Psoriasis	2055	Kaggle
4	Eczema	1677	Kaggle

Figure 2: Tabular representation of disease categories and image sources.

2.1.2 Train Test data Split:

In total, we have 15,975 images, and we intend to split them 80-20 between training and testing, which results in 12,780 images for training and 3,195 images for testing.

2.2 Data Cleaning and Pre-processing:

This phase involves reading the collected data, examining it for missing labels and unwanted images except for areas with lesion and healthy skin. Once the data has been cleaned, we will pre-process it to resize the image [7] without losing its quality, add some data augmentation since we have fewer samples to train the model with, and normalize the image for equally distributed samples.

2.2.1 Read image: A variable containing the path to the image dataset was created, and a function was created to load images from folders containing images into arrays.

2.2.2 Data Cleaning: Any training or analysis of data requires the cleaning of data as a key step. In the case, we already had a clean set of data for the images, with no missing labels, unwanted images, or noise, so the data did not need to be thoroughly cleaned for this process.

2.2.3 Resize image: There may be a variation in the size of the images captured by a camera and fed to the artificial intelligence algorithm, so we should establish a standard size for all images that we feed into the AI system.

2.2.4 Image Augmentation: An important technique in image processing, especially in computer vision, is data augmentation [8], which consists of applying random (yet realistic) transformations to training data to increase its diversity and amount. The images can be resized, rotated, flipped, and many other functions can be performed on them. A better training set is obtained by this technique, in turn resulting in a more effective model because of a more diverse nature of the data that has already been contained.

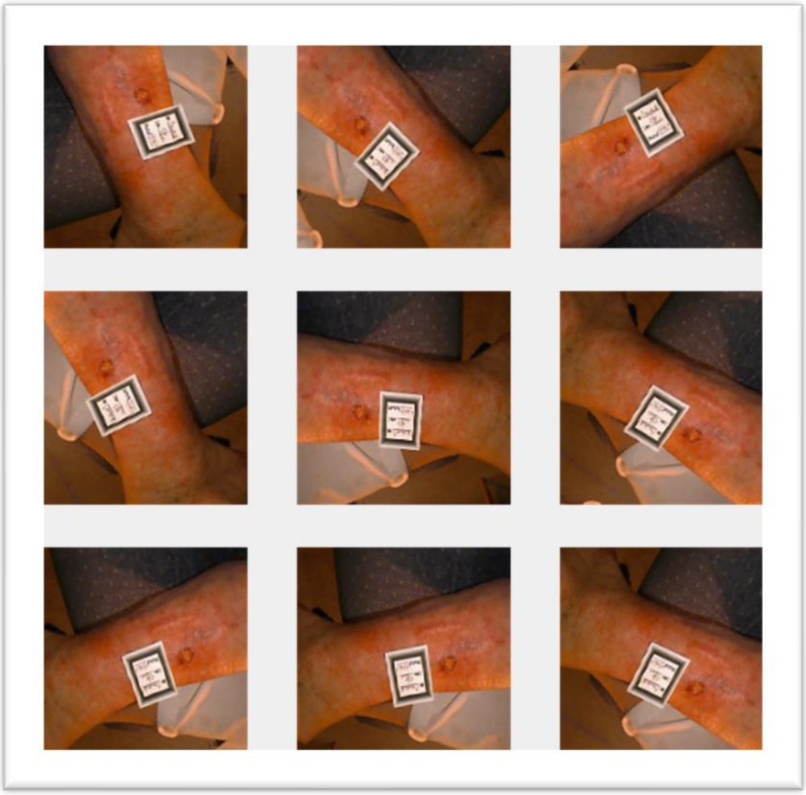


Figure 3: Visualisation of the image dataset after data augmentation copyrights provided on contractual agreement basis by Simon Hudson for project purpose.

2.2.5 Image Normalization: The process of data normalization [7] aims to ensure that each input parameter usually in pixels has a homogenous data distribution. As a result, the network converges more rapidly during training. As a rule of thumb, normalizing data involves subtracting the mean from each pixel and dividing the result by the standard deviation.

2.3 Model Selection:

In this project, we will be implementing machine learning algorithms and neural network architectures with hyperparameter tuning for model fitting and determine which algorithm is most suitable for diagnosing skin disease.

2.3.1 Machine Learning Algorithms:

(a) Random Forest Classifier: An algorithm for supervised machine learning that uses multiple decision trees built using random sampling based on bagging is the Random Forest Classifier [9]. There are two types of classification problems: Regression and classification and is based on majority voting and can be applied

(b) Support Vector Machine: The Support Vector Machine (SVM) is another supervised machine learning algorithm [10], which is most often used in determining the optimal hyperplane between for binary classification problems, the space can be viewed as an N-dimensional space (where N represents the number of attributes in the data).

(c) Naïve Bayes Classifier: Among the many types of classifiers, Naive Bayes [11] is the most effective for constructing faster machine learning models that can take fast predictions based on an object's probability and is referred to as a probabilistic classifier.

(d) Decision Tree Classifier: As well as being called the Classification and Regression Tree (CART) Algorithm, iteratively splitting the data from the root to the leaf nodes is the process of determining which direction the data should be analysed according to a decision tree [12]. For preventing overfitting, we can limit the maximum depth of the tree.

2.3.2 Artificial Neural Networks – Convolutional Neural network (CNN):

An integral part of the research will be the modelling of the scenario. For image analysis, a CNN with a multiple layer perceptron, robust to overfitting data, was constructed. For any convolution neural network or feed-forward neural network, the middle layers [13] are referred to as hidden layers because their input and output are masking by functions called activation functions and final convolutions and the true value of their nodes [14] is not known to the training dataset. Among these layers are those that perform the convolutions.

(a) Feature extraction using CNN: CNN's extract image features [21] from input images and is classified by another neural network. Feature extraction is carried out using the input image. As a result of the extraction of feature signals, a neural network is used to classify the data. Using the image features, the neural network classification produces the output. There are convolution layer piles and pooling layers included in the neural network for feature extraction. By utilizing the convolution process, the convolution layer transforms the image. It consists of digital filters in series.

(b) Pooling layers: By pooling layers, the attributes or features of a convolutional layer's output are minimized by keeping the highly influential characteristics and removing those that are less significant. Models extensively use maximum pooling and average pooling. When Max pooling is employed, the highest pixel is chosen among the group of pixels, whereas, when Average pooling is applied, the intermediate pixel is selected. The maximum pooling method is used where extreme attributes such as edges are necessary, whereas the average pooling method is committed when more general features are essential.

(c) Dropout rate: As part of the Dropout layer [19], input units are randomly set to 0 at a frequency of 0.5 at every stage of training, thereby lessening the likelihood of overfitting. A sum over all inputs is sustained by scaling up inputs not set to 0 by 1/ (1 - rate).

(d) Activation function: By computing weighted sums and adding bias, the activation function [20] determines whether to activate a neuron. A neuron's output is non-linearized through the activation function.

(e) Optimisers: Optimizers modify the weights and learning rate of a neural network by adjusting functions or algorithms. Doing so recedes the overall loss and improves the accuracy of the data. In terms of optimization, there is a wide spectrum of choices available, though RMSprop, Stochastic Gradient Descent (SGD) and Adam are the most typically used.

2.3.3 Hyper-parameter tuning:

By applying the cross-validation method to the predictive model, the GridSearchCV [15] method is applied to select the best parameters from a grid of parameters for better results.

2.4 Website Integration: To integrate CNN models into applications using Application Programming Interface (APIs), the following steps must be taken. Flask [22], a popular and lightweight framework for building web applications, will be used for API development with the help of Python. The API will receive requests from users in the form of an image. It will communicate with the model by transmitting the image for the machine learning algorithm to analyse and enables the user to view results on the website.

3. System Architecture

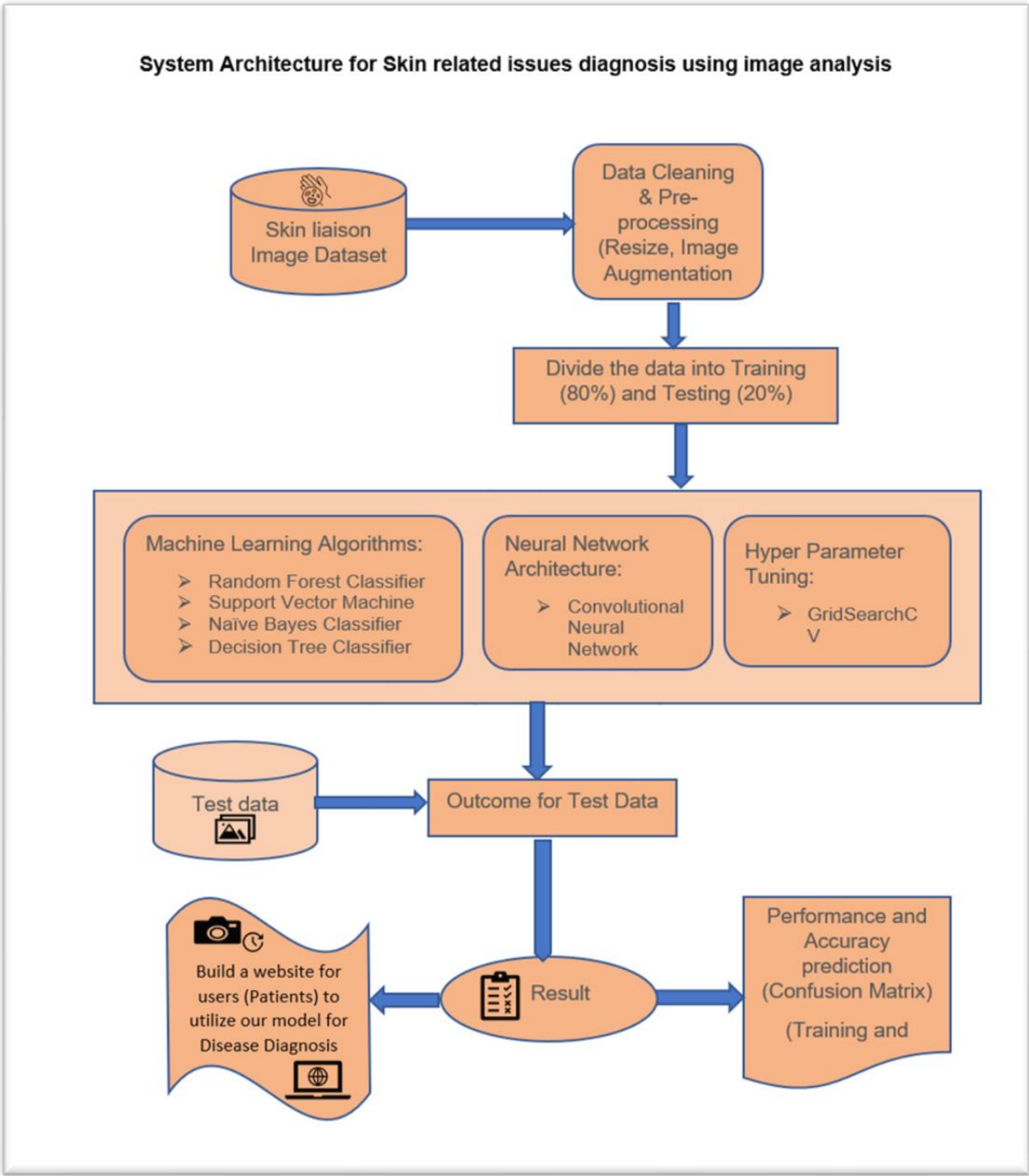


Figure 4: System architecture used in this model for Skin related issues diagnosis using image analysis.

4. Experiment

Several parameters will be taken into consideration to predict the accuracy of the experiment, including confusion matrix, the accuracy of training, the accuracy of validation, the precision, the recall, the F1 score, and the support.

(a) Confusion Matrix:

In addition to providing insight into the performance of a predictive model [16], the confusion matrix is also used to determine which classes are likely to experience type errors. Most of the time, this is a problem of two-class classification.

True Positive (TP): Specifically, this refers to the head count of patients who are categorised as having a specific skin disease, i.e., a true positive.

True Negative (TN): This identifies the head count of patients who do not have any skin disease and been diagnosed as do not have that disease.

False Positive (FP): It is the head count of patients who are misclassified as having a specific skin disease, which is referred to as a Type I error.

False Negative (FN): The head count of patients misclassified as not having any skin problems but having any category of skin conditions, also known as Type II errors.

(b) Accuracy:

In terms of performance, accuracy is a metric that indicates the percentage of instances that are correctly classified

An accurate prediction = (the number of correct predictions) / (the number of predictions overall)

Classification models based on binary data:

Accuracy = (TP+TN) / (TP+TN+FP+FN) [17]

(c) Precision and recall [18]:

A measure of precision is the ratio between the number of true positives classified and the number of false positives identified. In another formulation, recall can be described as the ratio of true positives to false negatives that are classified as true positives.

Precision: TP / (TP+FP)

Recall: TP / (TP+FN)

(d) F1 score:

This score is determined by combining the precision, recall, and weights of both the FP and FN to arrive at the F1 Score.

In the F1 Test, the score is calculated as 2 * (precision * recall) / (precision + recall)

(e) Support:

Support for a certain class in a dataset is measured by the numeral instances of that class. There is a possibility that the dataset needs to be sampled or rebalanced if the support is imbalanced.

5. Results

5.1 Analysis and Visualisation:

The following classifiers will predict the outcome of Skin disease. By predicting accuracy, we can decide whether a person falls into one of the skin disease categories.

(a) **Naïve Bayes:** There is a prediction that this classifier would be able to predict disease thirty -eight times out of one hundred. With the following, Naive bayes results:

[[3 1 1 1 0]
[1 2 0 3 0]
[4 3 2 1 1]
[1 0 1 4 5]
[1 1 0 0 4]]

(a) **Decision Tree:** According to predictions, this classifier has a 45 percent probability of being able to accurately predict disease on forty-five out of one hundred occasions. Based on the parameters supplied to us by the GridSearchCV method, we used {criterion = ['gini', 'entrop y'], max_depth = [2, 4, None], splitter = ['best', 'random']}.

(b) **Random Forest Classifier:** Approximately 35 percent of diseases can be accurately predic ted by the classifier. We used the GridSearchCV method using the parameters. {'n_estimato rs': n_estimators, 'max_features': max_features, 'max_depth': max_depth, 'min_samples_sp lit': min_samples_split, 'min_samples_leaf': min_samples_leaf, ‘bootstrap': bootstrap}. Three folds were fitted for each of the twenty-four candidates, totalling seventy-two folds in total

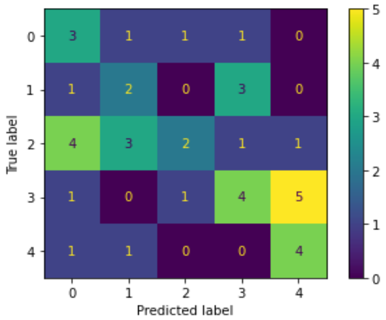
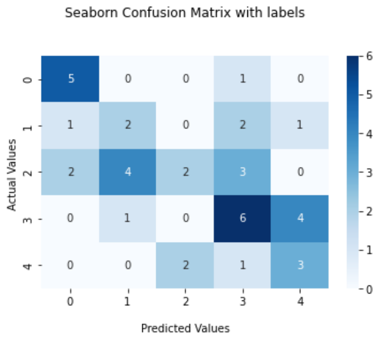
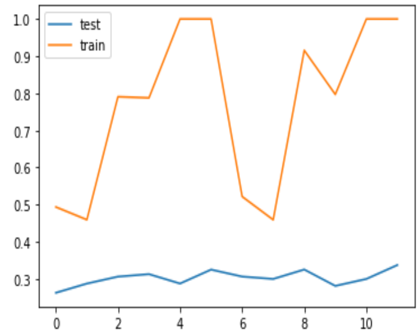
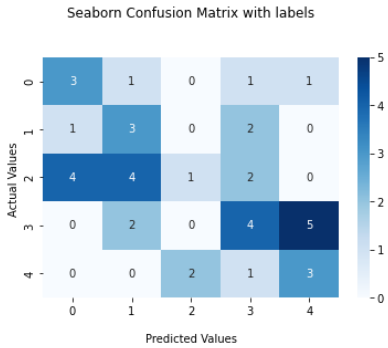
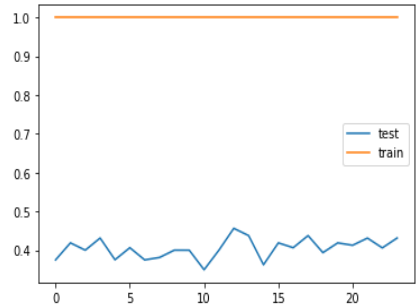
(c) Support Vector Machine: A prediction has been made that this classifier would be able to predict disease fifteen times out of one hundred in the statistical sense. We used the GridSearchCV method using the parameters {'C': [0.1, 5, 20], 'gamma': [0.1, 0.001, 1], 'kernel': ['rbf']}. A total of forty-five folds were fitted to nine candidates, each with five folds.

(d) Convolution Neural Network: For grid search we selected parameters as

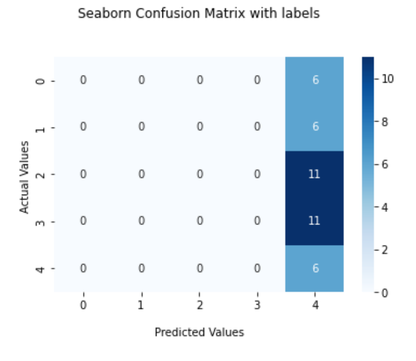
{'Batch size': 10, 50
'Epochs': 10, 30
'Dropout' 0.10, 0.20
'Pooling': Max, Average
'Activation Functions': relu, sigmoid, tanh
'Optimizer': Adam, RMSprop, SGD}

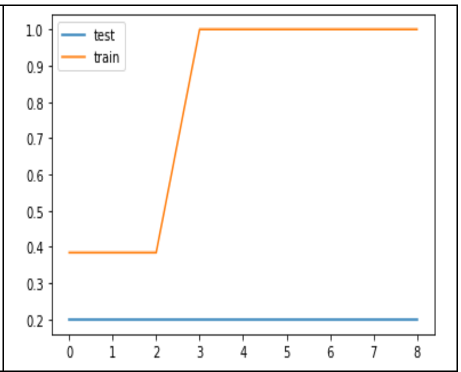
We obtained the best accuracy of 45 percent for batch size 50, 0.2 dropouts, with maximum pooling under relu activation and Adam optimization with thirty epochs

The final model was then trained using the best parameters to integrate with the website under twenty-five epochs with six layers, which generated a training accuracy of 85.72% and a validation accuracy of 73.18%.

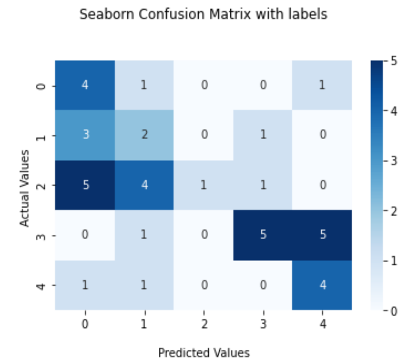
Algorithm	Confusion Matrix	Accuracy Plot
Naïve Bayes Algorithm		
Decision Tree Algorithm		
Random Forest Algorithm		

Support Vector Algorithm





Convolution Neural Network



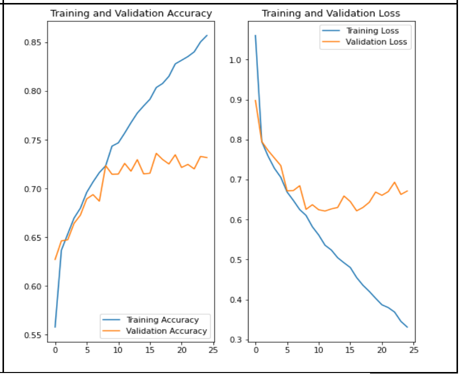


Figure 5: Confusion Matrix and Accuracy Plots for Algorithms.

Algorithms	Categories	Precision	recall	F1-score	support	Training Score (mean)	Validation Score (mean)
Naïve Bayes Algorithm	0	0.30	0.50	0.37	6	0.58	0.37
	1	0.29	0.33	0.31	6		
	2	0.50	0.18	0.27	11		
	3	0.44	0.36	0.40	11		
	4	0.40	0.67	0.50	6		
Decision Tree Algorithm	0	0.83	0.62	0.71	8	1.0	0.45
	1	0.33	0.29	0.31	7		
	2	0.18	0.50	0.27	4		
	3	0.55	0.46	0.50	13		
	4	0.50	0.38	0.43	8		
Random Forest Algorithm	0	0.50	0.38	0.43	8	1.0	0.35
	1	0.50	0.30	0.37	10		
	2	0.09	0.33	0.14	3		
	3	0.36	0.40	0.38	10		
	4	0.50	0.33	0.40	9		
Support Vector Algorithm	0	0.00	0.00	0.00	0	0.63	0.15
	1	0.00	0.00	0.00	0		
	2	0.00	0.00	0.00	0		
	3	0.00	0.00	0.00	0		
	4	1.00	0.15	0.26	40		
Convolution Neural networks grid search	0	0.67	0.80	0.73	5	1.0	0.57
	1	0.67	0.44	0.53	9		
	2	0.36	0.57	0.44	7		
	3	0.55	0.86	0.67	7		
	4	0.83	0.42	0.56	12		
Convolution Neural	0	0.31	0.67	0.42	6	0.97	0.4
	1	0.22	0.33	0.27	6		
	2	1.00	0.09	0.17	11		

networks	3	0.71	0.45	0.56	11		
final model	4	0.40	0.67	0.50	6		

Figure 6: Tabular comparison of the observations.

(e) Model Selection: Decision tree was the most accurate model at 100% of training accuracy and 45% of validation accuracy, indicating overfitting, and a neural network was the best model after hyperparameter tuning with GridSearchCV. The model that was trained with the best parameters had a training accuracy of 85.72% and a validation accuracy of 73.18% using the activation function "reLu" and the optimizer "adam". Detailed plots of the accuracy of each method can be found in Figure 7.

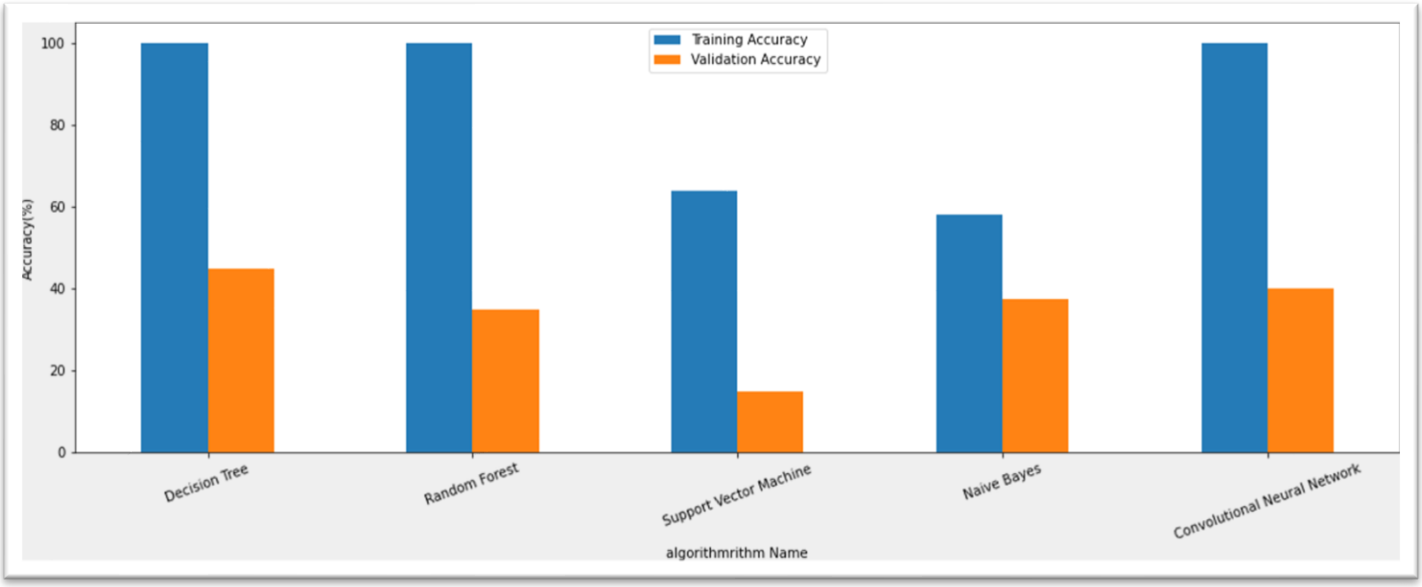


Figure 7: Performance comparison of the algorithms.

5.2 Visualisation: The final model's Accuracy and Loss plot can be found in Figure 8.

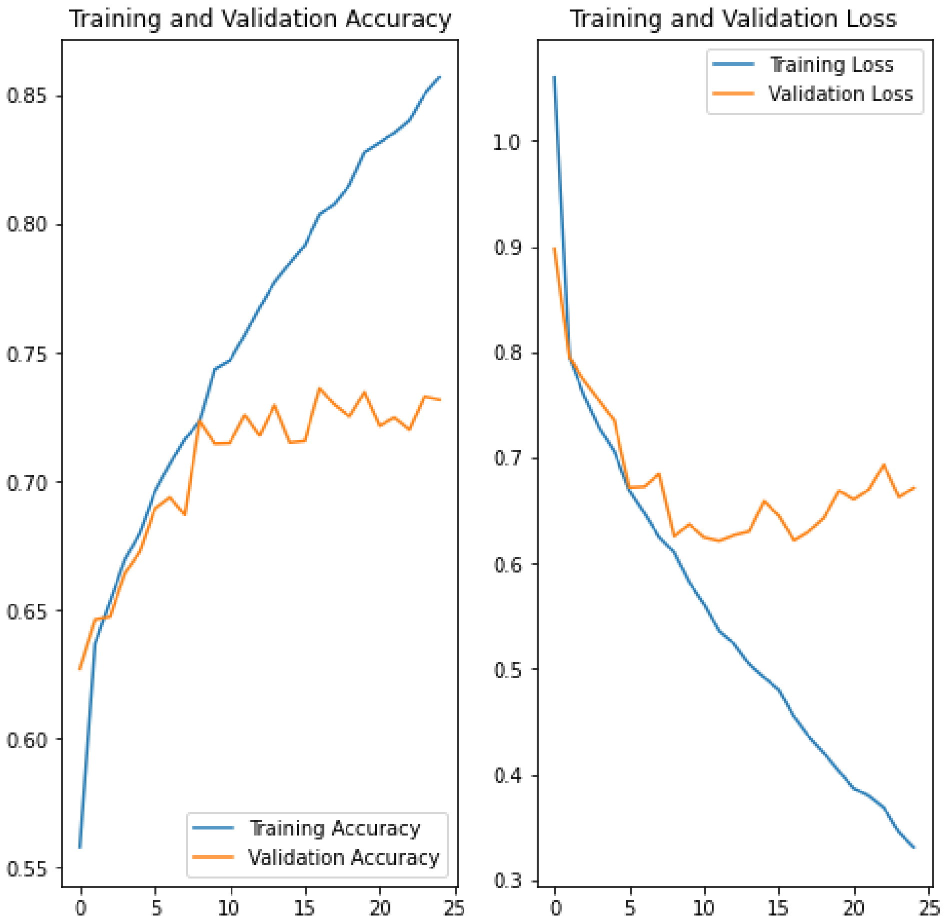


Figure 8: Training and Validation accuracy – loss graph.

5.3 Website:

This website has a basic interface that is amazingly easy to use even for a layperson. In the process of uploading an image, the user will be given the option to select the file from their device, and after uploading and submitting the image, the model is able to predict the category of disease that is likely to occur and advise the user of what to do next.

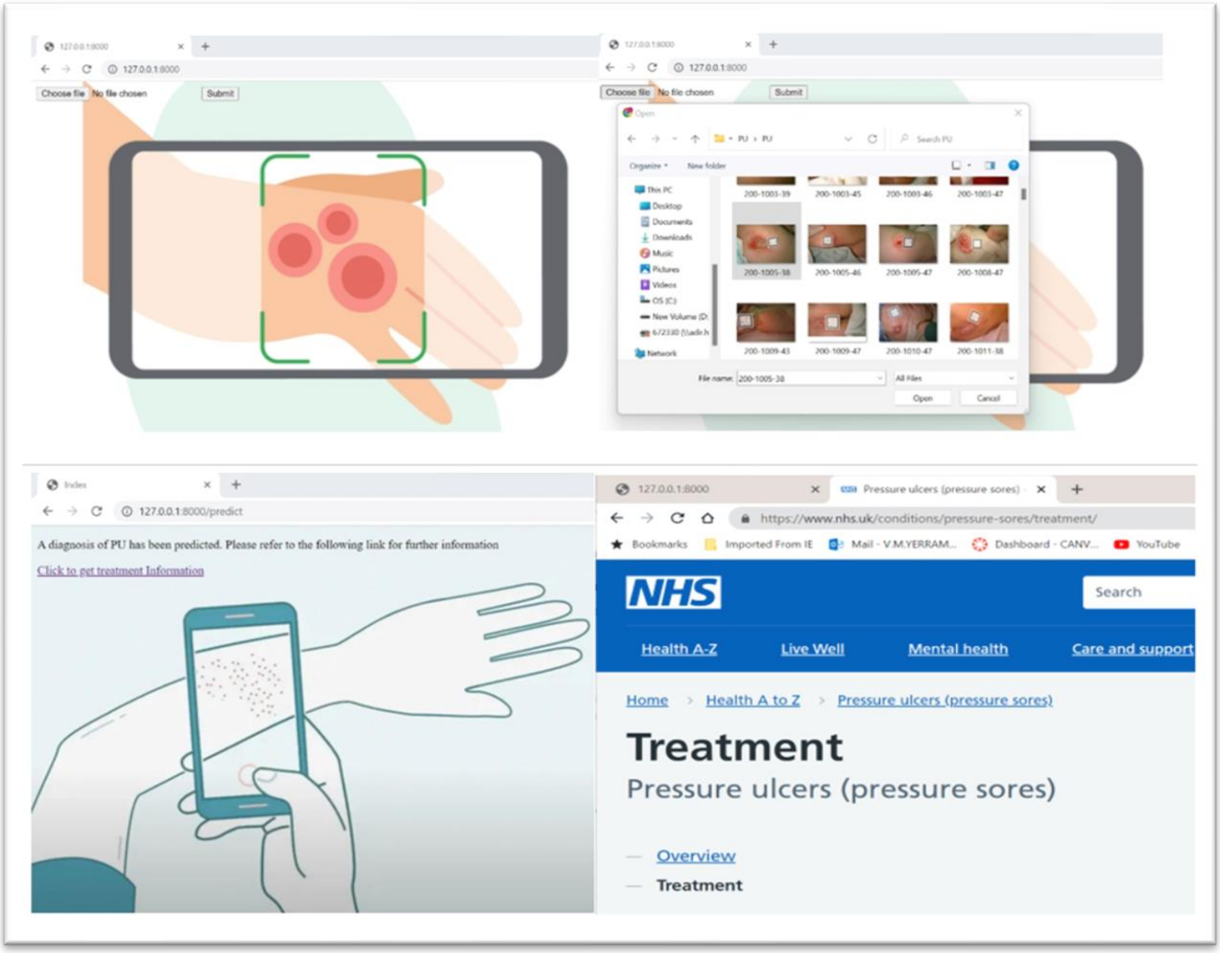


Figure 9: An overview of the website illustrating the steps involved in its usage.

6. Discussions

(i) How is data causing hardships throughout the world?

Cause of the continuous increase in the amount of data that can be analysed under the big data umbrella, traditional data analysis methods are not able to manage the continuous increase in the amount of data that can be analysed. This has led to the development of modern classification and regression techniques that are automated in their process. Adding deep learning to the mix requires an enormous amount of data, and that data is being generated daily. Medical research is heavily using neural networks to cut down on the number of people who are required to diagnose the ailment, thus cutting down on the costs.

(ii) In what manner is it necessary to use artificial intelligence to diagnose skin conditions?

Wounds and related problems affect millions of patients, resulting in high treatment costs. Those with chronic wounds (CW) are at increased risk for infection, amputation, and even death. The wounds of these patients require frequent hospitalization, but they do not have the ability to move about freely. Additionally, given many patients, it is not always feasible to conduct time-consuming quantitative wound assessments. Expertise and experience are incredibly important for accurate diagnosis and timely treatment. The ability to determine the progress and/or deterioration of the patient in a timely manner requires the use of a reliable diagnostic tool.

(iii) In what ways does the model contribute to the situation?

Skin disease can be diagnosed using the model without the use of heavy equipment. We are developing a model that can predict the results using a picture of the interaction taken with a smartphone, which is easily obtained in every household, and uploaded to the website to be used to predict the results. In addition to predicting the likelihood of a disease, the model also provides a link to the official website of the category of disease, which suggests what the user should do after predicting the disease.

(iv) What is the level of accuracy of the model?

A blend of machine learning algorithms and neural networks has been used to train the model. We were able to train the model more efficiently by using the augmentation technique. This was because we had access to more images, allowing us to make better use of the additional images. With multiple epochs and different pooling techniques, we were able to observe the model providing better accuracy, adding more layers, and fine-tuning some aspects to see what makes it better. With 25 epochs of training and validation, the model was 85.72 percent accurate for training and 73.18 percent accurate for validation. This was using a Max pooling technique, a reLU activation function, and an Adam optimizer. Our model has been trained up to sixty epochs, but we have noticed heavy overfitting. Thus, we confined the epochs to twenty-five in the calculations.

(v) Is there room for improvement in this area?

A computer with a small amount of Random Access Memory (RAM) cannot handle the data we have. Thus, we have only considered the first 2500 images. In addition to its limited memory and huge amount of data, the laptop's limited resources made adding the augmentation technique to the program quite a challenge. In addition, when running the Python program, the browser crashed several times, compromising the accuracy of the model since we could not use all the data available. If the model is provided with the right amount of power and an improved environment, then there is a good chance that it can achieve close to 95 per cent accuracy.

7. Conclusions and Future enhancements

As technology progresses and neural networks are increasingly being used in medical science, artificial neural networks will become a powerful tool for handling copious quantities of data. By collecting the data and training the data using the model as reference, the predicted model can be applied to various other diseases such as cancer, diabetes, heart disease and other common diseases. Based on the training and validation accuracy, decision tree was the most accurate model, indicating overfitting, and neural network was the top model after hyperparameter tuning with GridSearchCV. By using the activation function "reLu" and the optimizer "adam", the model was trained with an accuracy of 85.72% and validated with an accuracy of 73.18%. We anticipate that the model can be implemented in future mobile applications through the integration of an API framework and an algorithm integrated into a mobile application. Users will be able to complete attributes by uploading a photograph of the wounded skin and predict the likelihood of pruning based on the appearance of the diseased skin.

8. References

[1] Ieeexplore.ieee.org. 2022. Dermatological disease detection using image processing and artificial neural network. [online] Available at: [Accessed 23 April 2022].

[2] ALEnezi, N., 2019. A Method of Skin Disease Detection Using Image Processing and Machine Learning. Procedia Computer Science, 163, pp.85-92.

[3] Arifin, S., Kibria, G., Firoze, A., Amini, A., & Yan, H. (2012) “Dermatological Disease Diagnosis Using Colour-Skin Images.” Xian: International Conference on Machine Learning and Cybernetics.

[4] Sumithra, R., Suhil, M. and Guru, D., 2015. Segmentation and Classification of Skin Lesions for Disease Diagnosis. Procedia Computer Science, 45, pp.76-85.

[5] Harangi, B., 2018. Skin lesion classification with ensembles of deep convolutional neural networks. Journal of Biomedical Informatics, 86, pp.25-32.

[6] Kaggle.com. 2022. *Skin diseases image dataset*. [online] Available at: <https://www.kaggle.com/datasets/ismailpromus/skin-diseases-image-dataset> [Accessed 10 August 2022].

[7] Medium. 2022. *Image Pre-processing*. [online] Available at: <https://prince-canuma.medium.com/image-pre-processing-c1aec0be3edf> [Accessed 10 August 2022].

[8] 2022. [Blog] Available at: <https://www.analyticsvidhya.com/blog/2021/05/image-classification-with-tensorflow-data-augmentation-on-streaming-data-part-2/#:~:text=What%20is%20Data%20Augmentation%3F,Image%20flip%2C%20and%20many%20more> [Accessed 10 August 2022].

[9] En.wikipedia.org. 2022. *Random forest - Wikipedia*. [online] Available at: <https://en.wikipedia.org/wiki/Random_forest> [Accessed 10 August 2022].

[10] GeeksforGeeks. 2022. *Introduction to Support Vector Machines (SVM) - GeeksforGeeks*. [online] Available at: <https://www.geeksforgeeks.org/introduction-to-support-vector-machines-svm/#:~:text=Support%20Vector%20Machine%20%28SVM%29%20is%20a%20relatively%20sim> [Accessed 10 August 2022].

[11] www.javatpoint.com. 2022. *Naive Bayes Classifier in Machine Learning - Javatpoint*. [online] Available at: <https://www.javatpoint.com/machine-learning-naive-bayes-classifier#:~:text=Na%C3%AFve%20Bayes%20Classifier%20is%20one%20of%20the%20simple,t> [Accessed 10 August 2022].

[12] Medium. 2022. *Decision Tree Classification*. [online] Available at: <https://medium.com/swlh/decision-tree-classification-de64fc4d5aac#:~:text=%20Decision%20Tree%20Classifier%20%201%20Using%20the,We%20co> [Accessed 10 August 2022].

[13] En.wikipedia.org. 2022. *Convolutional neural network - Wikipedia*. [online] Available at: <https://en.wikipedia.org/wiki/Convolutional_neural_network> [Accessed 10 August 2022].

[14] Deepomatic. 2022. *Introduction to deep learning - AI for dummies (2/4) - Deepomatic - Visual Automation Platform*. [online] Available at: <https://deepomatic.com/introduction-to-deep-learning-ai-for-dummies-2-4> [Accessed 10 August 2022].

[15] Python, H., 2022. *How to Use GridSearchCV in Python*. [online] Datatechnotes.com. Available at: <https://www.datatechnotes.com/2019/09/how-to-use-gridsearchcv-in-python.html> [Accessed 10 August 2022].

[16] Brownlee, J., 2022. What is a Confusion Matrix in Machine Learning? [online] Machine Learning Mastery. Available at: <https://machinelearningmastery.com/confusion-matrix-machine-learning/#:~:text=A%20confusion%20matrix%20is%20a,two%20classes%20in%20your%20datase> [Accessed 10 August 2022].

[17] Google Developers. 2022. Classification: Accuracy | Machine Learning | Google Developers. [online] Available at: <https://developers.google.com/machine-learning/crash-course/classification/accuracy> [Accessed 10 August 2022].

[18] scikit-learn. 2022. Precision-Recall. [online] Available at: <https://scikit-learn.org/stable/auto_examples/model_selection/plot_precision_recall.html#:~:text=Precision%20(> [Accessed 10 August 2022].

[19] 2022. [Blog] Available at: <https://keras.io/api/layers/regularization_layers/dropout/#:~:text=The%20Dropout%20layer%20randomly%20sets,over%20all%20inputs%20is%20unchanged.> [Accessed 14 August 2022].

[20] 2022. [Blog] Available at: <https://www.geeksforgeeks.org/activation-functions-neural-networks/> [Accessed 14 August 2022].

[21] 2022. [Blog] Available at: <https://www.sciencedirect.com/topics/computer-science/feature-extraction-network#:~:text=CNN%20is%20a%20neural%20network,the%20neural%20network%20for%20classification.> [Accessed 15 August 2022].

[22] En.wikipedia.org. 2022. *Flask (web framework) - Wikipedia*. [online] Available at: <https://en.wikipedia.org/wiki/Flask_(web_framework)> [Accessed 15 August 2022].