Mobile Medical Assistant and Analytical System for Dengue Patients

*Abstract*—Dengue fever is a viral vector-borne disease spread by the mosquito Aedes Aegypti. It is a public health problem, with an estimated 50 - 500 million infections each year and no effective vaccination. Due to people's hectic schedules, they may not have enough time to see a doctor every time they have a fever. They may overlook their disease, believing it to be a common ailment. Therefore, prior medical assistance for patients with fever to check their conditions in a reliable way is a prominent need. This paper presents a mobile medical assistant and analytical system- for dengue patients. The designed mobile application supports identifying dengue patients using chatbot, analyzing dengue infected areas, analyzing skin conditions and analyzing blood report functionalities. The patients need to log in and enter their details to check their dengue condition. All the data are stored in the database: The development is carried out with Natural language processing Machine Learning, Convolutional Neural Network (CNN), Artificial neural network and Android technologies. A mobile application prototype is created and tested, with the possibility of future testing and implementation. The results show effective performances in analyzing dengue conditions.

Keywords—Dengue fever, Medical Assistant, DHF, infection, symptoms

# Introduction

Dengue hemorrhagic fever (DHF) and dengue fever (DF) cases have risen rapidly in recent decades, posing a global danger. The World Health Organization estimates that 500 million cases of DF and 250,000–500,000 cases of DHF occur each year. Dengue fever has become a deadly disease in recent years. Detecting this fever in its early stages and gaining a thorough understanding of its present health status by studying its medical variables and symptoms is a huge challenge. In recent years dengue has become a fatal disease in Sri Lanka. There were a total of 31162 presumed dengue cases for the year 2020 and 12231 suspected dengue cases were reported to the Epidemiology Unit from all over the island from January 2021 to up to now. The dengue cases reported in the Western province were at a rate of 15.0 percent. In 2017, Sri Lanka faced the worst dengue outbreak [1]. During the 29th week of 2017, the maximum number of dengue cases was reported. Figure 1 shows the reported dengue cases in the past 6 years in Sri Lanka. It is critical to seek medical assistance if the user have a fever and to have necessary laboratory tests done by day three of the sickness.

1. Reported dengue cases from 2015 to 2020

This virus (40°C/104°F) is accompanied by two or more of the following symptoms: severe headache, discomfort behind the eyes, muscle and joint pains, nausea and vomiting, and a skin rash. Symptoms often emerge 4-10 days after an infected mosquito bite and last 2-7 days. People suffering from dengue fever are recommended to relax, drink plenty of water, and take paracetamol to reduce their fever. It is critical to get admitted to a hospital as soon as possible if the situation worsens. Due to significant bleeding, plasma leakage, fluid accumulation, or organ dysfunction, severe dengue, or dengue hemorrhagic fever (DHF), can be fatal. Severe abdominal pain, persistent vomiting, quick breathing, bleeding gums, exhaustion, restlessness, and blood in vomit appear 3–7 days after the first symptoms, coupled with a drop in temperature (below 38°C/100°F). Dengue fever and DHF complications can be avoided with early detection and adequate medical treatment [2]. There is no suitable system in place to identify Dengue patients at the early stage, provide them with information about their current health, and lead them toward appropriate treatment options.

Early detection and treatments for this virus can help to reduce morbidity and mortality. Dengue illness (Dengue Fever - DF/Dengue Hemorrhagic Fever - DHF) is being considered in the differential diagnosis of patients presenting with acute onset of fever, headache, retro-orbital pain, myalgia, arthralgia, and rash hemorrhagic manifestation in the current hyper-endemic setting in Sri Lanka. Complications can be avoided if the signs are detected at the early stage. Dengue patients are suffering from major health problems as a result of a lack of effective health monitoring [3].

Remote diagnostic systems are becoming more common and precise as technology advances, offering various benefits such as cost-effectiveness and speedy and reliable support for medical diagnostic decisions. The project's goal is to create a chatbot system that can be easily accessed by users to identify Dengue patients at the early stage and provide them with information about their current condition without wasting time. As medical technology becomes more innovative, medical expert systems that forecast and manage diagnosing procedures will be required. Medical diagnostic processes using technology to properly identify ailments when evaluating patient data in order to make effective decisions, as well as Chabot, have shown promise in improving people's health. In today's world, mobile chats are becoming the norm.

The rest of the paper is structured as follows. The second section discusses the existing systems related to Dengue Patients. The third sections represent the proposed system methodology with its main features. The fourth section evaluated the obtained system results and discuss the further improvements in development. The last section concludes the research works of the system.

# Literature Review

Over the years, many researches have been carried out to address the problems related to dengue Virus. Vt there are only few ideas proposed for the assistant and benefits of dengue patients. The advanced technological development has provided greater benefits to implement such systems. In 2019, a system is proposed for skin condition detection with image processing and machine learning techniques [4]. The system supports expert mediation and a framework for analyzing skin diseases utilizing shading photographs. The framework is separated into two phases: the first is the identification of infected skin using shading image processing procedures, such as k-implies bunching and shading slope approaches, and the second is infection type categorization using fake neural organizations. The detection of the system was designed with the use of the Alexa Net convolutional neural network model and Support Vector Machine. The system was implemented using MATLAB software. The framework was put to the test on six different skin conditions, with the first-stage precision of 95.99 percent and a second-stage precision of 94.016 percent. Zeljkovic et al. [5] proposed a Melanoma detection device for brown complexions based on specialized computation data sets that included photographs from a variety of Melanoma assets that are a type of skin cancer in 2015. A variety of skin cancer images were used in the system to develop an algorithm. The system implementation was carried out in three steps as a colour image to grayscale conversion, applying edge detections and image enhancing. The system acquired more than 5% accuracy in the image classifications. The tool applies to the initial pre-screening of the broader population tool by general medical staff.

Anno et al. [6] proposed Early warning systems (EWS) to determine how to control and prevent dengue fever outbreaks in Taiwan in 2019. The search for parameters with a spatiotemporal link with dengue fever epidemics was aided by machine learning. The town-level emerging dengue fever hotspots were examined by conducting an analysis. Machine Learning techniques and a Convolutional Neural Network model were trained for the proposed system. The hotspots analysis was conducted via ArcGIS 10.4.1. Through this analysis, the dengue fever spreading patterns and outbreak projections were examined. According to the results, the analysis showed a direct connection between rainfall and dengue outbreak. The test data represented 100% accuracy in the evaluated system performances. In 2018, an Extreme Learning Machine Method for Dengue Hemorrhagic Fever Outbreak Risk Level Prediction project was implemented by Najar and others [7]. The system creates ELM architecture with weather variables as input nodes and DHF outbreak risk level as a target. They employ a bipolar sigmoid with several hidden neurons ranging from 5 to 200 nodes and a binary sigmoid activation function. The system consists of three main processes as acquisition and pre-processing of data, training and testing. Monthly weather and dengue haemorrhagic fever data have been used for the system. The system performances showed that the system model is suitable for the DHF predictions.

A mobile application is designed and developed in 2018 to analyse dengue attacks in Malaysia [8]. The application is developed for both patients and hospital users. The registered users can check their conditions through the App. The user needs to enter the blood test and temperature level data tested using a dengue kit to the application. Microsoft Azure is used as the data storage tool and the hospital can monitor the patient’s data through a web page. After entering the data if the condition is critical, the application issues a warning alert and gives advice. If the condition is not critical then the application provides advice. The system has been tested and evaluated for 20 patients in Malaysia. In 2015, a case study for fever monitoring and tracking has been carried out by a mobile application development [9]. The system is designed for Fiji Island with the help of mobile phone technology. The system supports a dengue-infected area map that helps authorities to take quick actions. The application consists of four main features, user authentication, dengue symptom checking, confirmed case reporting and feedback support. The feedbacks are based on traditional medication which is giving papaya leaves extracts. All the user data is directed to the database and presented through a map on a website. Technologies such as Android, Java LAMP Server, PHP have been used for the developments. The system tested with 10 mobile phone users and a dengue map is generated with collected data. A chatbot, also known as a conversational agent, is a computer program that engages in natural language interaction with a user and delivers some type of service . Chabot provides intuitive and accessible human-computer contact and is thus widely utilized in areas such as customer service, e-commerce, education and learning, information retrieval, and more. Healthcare (Section 2.2.1) in WHO dengue diagnosis publication in 2021 is a common topic in scientific writing [10]. Chatbots are often goal-oriented, meaning they are trained to fulfil requests related to a single area (closed domain).

In 2021, an Artificial Intelligence technology is applied to implement a medical chatbot that gives the patient a sickness diagnosis and then gives them complete information about the disease [11]. The user's input is matched for symptoms, and the system generates a shortlist of possible diseases based on these symptoms. The chatbot then asks further questions to validate the diagnosis and presents a shortened list until a definitive diagnosis is reached. In the event of a major ailment, the symptoms' data will be submitted to a professional. For lesser illnesses, the bot recommends first aid and a trip to the doctor. Riech et al. discussed the challenges in the dengue infection prediction system with the Thailand case study in 2016 [12]. A model was developed for the real-time forecasting of dengue hemorrhagic fever. The system involves methods such as real-time data management, delay accounting, time predictions, etc. The disease model was implemented as a statistical model for the result estimation. The real-time model data was compared with manual report data and evaluated the system challenges.

# Methodology

Diagram

Description automatically generatedThe mobile application is designed with four main functions. Figure 2 represents the high-level architecture of the system. All the registered users can receive the medical assistant through the App. The implementation of the system was carried out using Image processing and Machine learning techniques.

1. Overall system architecture.

## Patient Identifying and Classifying Chatbot

Chatbot gives the symptom information and identifies the condition of the user. It helps to reduce the patient’s complications by identifying the disease at an early stage. At first, the chatbot gathers the user's symptom data and text inputs via a questionnaire. Then the collected data (qualitative and quantitative data) are stored in the datastore and analysed to give the output. The results are presented in terms of the dengue stage as No Dengue Fever, Normal Dengue Fever, Dengue Hemorrhagic Fever or Dengue Shock Syndrome.

The chatbot can be divided into three main functional modules as pre-processing, feature extraction and classification. To get an affirmative response, the questions are in yes or no format (0 or 1) and the user will be able to add additional symptoms as a text input. The inputs are created as labelled 2D arrays. The phase optimization is achieved at the pre-processing stage. The text pre-processing is accomplished by using Natural Language Processing (NLP) techniques. When the user sends symptom's information, the system receives it and transmits the text to the NLP module, which examine the text, and relevant keywords are extracted. Then tokenized the dataset. In the pre-processing stage the noise/ stop words of the dataset are also removed.

The word embedding techniques are used to transform keywords into feature vectors. The feature vectors are later applied together with the machine learning algorithms. The pre-processed text inputs can be distinguished as feature vectors. Fuzzy string matching is used in the key word extraction process. The model is trained with the Naive Bayes classifier. The data processed by the NLP module is used to train the classification model. At last, the classification model receives the feature vectors and the chatbot will send the results to the user by completing classification.

Unlike Other chatbots, this system gives immediate and accurate output to the user. Dengue Stages classified through a custom Artificial Neural Network (ANN) classification model. ANN is important in identifying complex patterns with large number of inputs. The NLP model is an important component in the chatbot. NLP and Natural Language Understanding techniques are embedded in the system for efficient response. Human languages can be read, decode and interpret with the use of NLP. Apart from the above techniques. the chatbot development included python technology stack, with additional machine learning libraries. The Model is built with 3 hidden layers with ‘Relu’ as the activation function, the output layer is dense. The final layer use ‘Softmax’ as an activation function. The collected dataset is used to train the model and used ‘adam’ as the Optimizer. 'Sparse\_categorical\_crossentropy' function used as the Loss calculation function. By referring to the distinct characteristic data, the model classifies the user input as “No Dengue Fever, Normal Dengue Fever, Dengue Hemorrhagic Fever or Dengue Shock Syndrome” and provides the output.

## Identifying and Analyzing Dengue Infected risk Areas

Through dengue infected area analysis, the user can get to know the infected locations via a dynamic map. The module is implemented with the past and real-time weather forecast data. This module provides three services to the user such as analysis of infected areas, visualization of infected areas and sending notifications to the user. After analysis, the users can view those analyzed infected risk areas in an inbuilt map. The application requires the user location permission to enable the

notifications. Using the GPS of the mobile, the application sends a notification if the user is in a risk area or if the user entered a risk area. And also, if a registered user is identified as a dengue patient, all the user details together with the location will be added to the application database. Then the application infected area map will be updated with the information.

The Data set combined with the daily Rainfall data collect from Meteorology Department and Infected cases data collected from MOH (Ministry of Health). From there data collected for 10 years with different seasons in Sri Lanka. The data set has six columns which include city, year, month, date, rainfall, and Infected Cases. The phase optimization is achieved at the pre-processing stage. Unlike Other risk area prediction systems this system gives accurate output to the users. Predict risk Ares through a custom neural regression model using Keras Regressor. NN (Neural Network) is important in identifying non liner complex patterns with large number of inputs. Compare neural regression model with the Multiple Linear Regression model and LASSO Regression models the highest accuracy shows neural regression model: rainfall and infected cases have complex pattern.

## Analyzing Skin Conditions

Through skin condition analysis, the system identifies whether the patient is dengue infected or not. The users can easily upload their skin images to the mobile application and get the output. The Model was developed with trained machine learning algorithms and image processing. The input images are analyzed through the developed model. The analysis is conducted in terms of allergies, rashes and abnormalities in the skin. The system is trained with the above conditions to identify the user condition. The user is identified as a dengue patient if the input image matches with the system identification process.

The system comprises three main operational functions namely pre-processing, feature extraction and classification. Image resizing is used as a pre-processing technique to generate high performance in the Model. Different image sizes in the database can cause a lot of problems. So the images are resized to a static resolution. In this system, all images are set to 450 x 450 pixel size. Thus, it gives high system performance, less processing time and the same no of image features. This image size can be improved with a high- performance system environment. The features of input images are extracted through a custom made Convolutional Neural Network (CNN) model using Keras. CNN is known for good feature extraction and its efficiency is well above other neural networks. And also, CNN supports feature learning and weight sharing. After feature extraction, the images are classified as infected and non-infected. The next step was to select the suitable CNN Architecture.

After working with many CNN architectures such as Alexnet, Vgg16, Vgg19, Restnet50, InceptionV3, VGG16 showed better performance and better results against earlier mentioned models. The Model is built with 16 hidden layers with ‘relu’ and ‘softmax’ as the activation method and pooling layers of (2,2) size and (3,3) kernel size. 350+ RGB images are used to train the model with 40 epochs and ‘adam’ as the Optimizer. The Loss calculation method used here is 'sparse\_categorical\_crossentropy' and the image data sets are generated using the ‘ImageDataGenerator’ method and saved in ".h5" format. By referring to the distinct characteristic data the model classifies the user input as “Dengue Infected” or “Not Infected” and provides the output via mobile application.

## Analyzing Blood Reports and Severity Identification

This module supports application users to check whether he/she is dengue infected person with their blood report analysis. When the user uploads their full blood count report, the system analyzes it based on the patient's platelet count, white blood cells count and some other necessary parameters. The report is analyzed through image processing and machine learning techniques. The user receives the final output of the blood report in the present dengue stage from the four fever categories.

The operation of this module can be divide into three steps. At first, the uploaded blood report image is pre-processed for optimization. The image is cropped and resized to remove unnecessary parts. Then a white mask will be applied to the blood report to remove the background of the report. The procedure consists of dilation and erosion. The edges of the report are increased with the canny threshold technique and given it a gray colour. Ridge regression (RR) is applied to train and build the system model. Among the tried and tested models, it has a high level of accuracy. The model is used to validate the values returned by the report.

The pre-processed image is then moved to the Google Optical Character Recognizer (OCR). Google OCR is technology that works through Google Cloud Vision API. Under the feature extraction stage, Google OCR separates the text of the document into sections and identifies the location and the text separately. Then a keyword search algorithm is applied to detect these specific words like White Blood Count(WBC), Platelet count (PLT) and Haemoglobin (HGB) values in the report. After validating, the accurate values in the report are displayed as output. Then these output values are compared in the classification part and get the severity. At last, the current dengue stage is presented to the user from the four categories below,

* Not in dengue fever
* Normal dengue fever.
* Dengue hemorrhagic fever.
* Dengue shock syndrome condition.

Also, using blood values, the classification part of this shows the present stage of the dengue patient. This model is based on the values of WBC, HGB, and PLT. The Decision Tree classifier is used to train the model. For this few different classification models were tried and among them try to select best one based on accuracy and less errors. Finally, the classification model receives the values from the dataset and sends the results to the user after completing classification.

The machine learning module of the system is trained with a training dataset of blood reports. The development was carried out via a location-based machine learning approach.

# Results and Discussion

In the patient identifying and classifying chatbot, first, the system gets the user input through the questionnaire. To achieve the accuracy relatively high, the system gets more user inputs related to the symptoms and then generates the response. The evaluated system performances depicted a low value for the model loss. Thus, providing efficient outcomes from the chatbot.Chart, line chart

Description automatically generated The model is important in identifying complex patterns with large number of inputs.

1. Model accuracy in patient identifying and classifying chatbot

Figure 3 depicts how training and testing accuracies changes according to no of epochs.

1. Accuracy Variation Table

| Accuracy | No of epochs | No of hidden layers |
| --- | --- | --- |
| 53.49% | 10 | 2 |
| 62.24% | 20 | 2 |
| 79.58% | 30 | 2 |
| 88.71% | 40 | 2 |
| 67.30% | 10 | 3 |
| 79.96% | 20 | 3 |
| 88.75% | 30 | 3 |
| 97.09% | 36 | 3 |

Table 1 demonstrates how accuracy values changes according to number of epochs and number of hidden layers. The accuracy value increases with the number of epochs and number of hidden layers. In the Dengue Patient Identifying and Classifying Chatbot System, the ANN neural network model achieved 97.09% accuracy.

1. Accuracy Variation Table

| Average accuracy | No of epochs | No of hidden layers |
| --- | --- | --- |
| 65% | 10 | 2 |
| 71% | 15 | 2 |
| 71% | 20 | 2 |
| 83% | 20 | 3 |
| 91% | 30 | 3 |

Table 2 demonstrates how accuracy values changes according to number of epochs and number of hidden layers. The accuracy value increases with the number of epochs and number of hidden layers. In the Identifying and analyzing infected risk area System, the neural regression model achieved 91.04% accuracy.

The development an infected area analysis, the model has been trained and acquired the regression output. In the training model, the results show a decrease in model loss parameters. The Model is built with three hidden layers with ‘relu’ as the activation method and 30 epochs. The mean squared error loss function used as the loss calculation function and ‘adam’ as the Optimizer. Using location and date information the system will predict risk dengue zones and visualize in the map.

Chart

Description automatically generated

1. Model accuracy in infected area prediction

Figure 6 shows the deviation of model loss in terms of testing & training data. Model loss depicts the quality of the model prediction and zero model loss represents the perfect predictions. The model showed an overall accuracy of 91.84% as the output. The dengue patients who check their dengue condition with other application functions are added to the database for the use of this prediction model.

Chart, line chart

Description automatically generated

1. Model loss in infected area prediction

The skin condition analysis function, the accuracy is evaluated in training data and testing data. First, the training data accuracy is evaluated and then predicted the results from test data. Then the validation accuracy is obtained by comparing the prediction and test data results. According to the input, the system provides whether the user is dengue infected or not. The model testing has shown an efficient and accurate system performance.

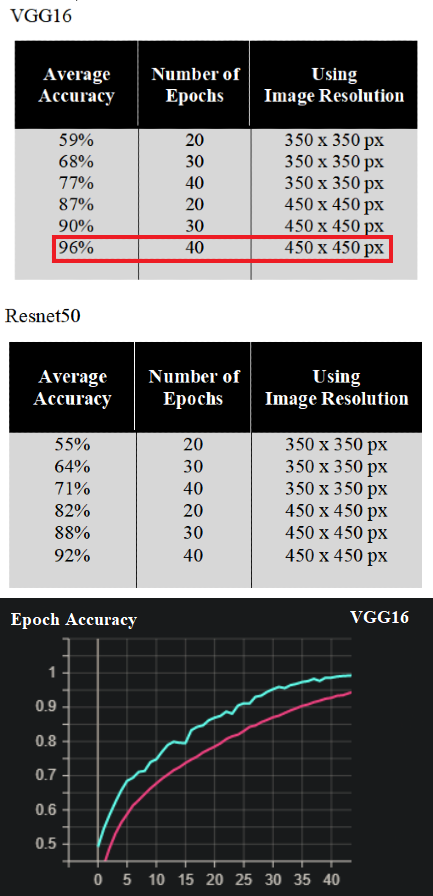
Table 3 and Table 4 shows the average accuracy variation which states the performance between VGG16 and Restnet50 which the two models showed close accuracy levels occurred by changing two major variables when training the model and Figure 8 shows the variation of accuracy level of VGG16 against the number of epochs. The ‘Blue’ line and ‘Red’ line represent ‘training accuracy’ and ‘validation accuracy’ respectively.

1. Accuracy Variation Table VGG16

| Average accuracy | No of epochs | Image Resolution |
| --- | --- | --- |
| 59% | 20 | 350 x 350 px |
| 68% | 30 | 350 x 350 px |
| 77% | 40 | 350 x 350 px |
| 87% | 20 | 450 x 450 px |
| 90% | 30 | 450 x 450 px |
| 96% | 40 | 450 x 450 px |

1. Accuracy Variation Table Restnet50

| Average accuracy | No of epochs | Image Resolution |
| --- | --- | --- |
| 55% | 20 | 350 x 350 px |
| 64% | 30 | 350 x 350 px |
| 71% | 40 | 350 x 350 px |
| 82% | 20 | 450 x 450 px |
| 88% | 30 | 450 x 450 px |
| 92% | 40 | 450 x 450 px |



1. Accuracy variation graph

Since the model accuracy charts did not show signs of model overfitting. Regularization is not required for this image classification model. The VGG16 CNN model provides an accuracy of 96% as per the figure 8.

The blood report analysis system operates the location-based machine learning approach, and the testing records the system accuracy. The Google OCR identifies the text list from the reports with the location. The evaluated system performances showed an increasing accuracy rate with more testing phases. The ridge regression model showed an overall accuracy (R2 score) of 99% as the output. And the classification part of the system, the Decision Tree classifier provides accuracy as 96 %.

Chart, bar chart

Description automatically generatedA correlation matrix is a table showing correlation between variables. Each cell in the table shows the correlation between two variables.

1. Heat map of ridge regression
2. Decision Tree Classifier

This decision tree considers about WBC, HGB & PLT counts to determine the patient severity.

Overall, the application supports identifying dengue-infected areas, analyze skin conditions, identify user conditions and analyze blood reports. The mobile medical assistant and analytical system for dengue patients are developed by allowing users to enter their blood reports, skin conditions, symptoms, locations and to receive an immediate response. The application helps as a medical assistant to prevent ddengue patients suffering from serious health issues with the situations they need to face. The relevant authorities like MOH can get great use from the infected area map. The ability to use a smartphone or tablet to check the dengue conditions provides a great advantage for the users.

# Conclusion

This paper presents an analytical mobile medical assistant for dengue patients. The proposed mobile application provides more convenient services for dengue patients to identify their condition. A dengue patient can upload their blood report and find their dengue stage, a person with normal fever or some related symptoms can add their symptom information and check the condition, a patient can use their skin images to identify the condition and finally user can get informed with dengue infected areas through a dynamic map. The implemented system ideally used ANN classification model for patient identifying and classifying chatbot, VGG16 CNN Model or analyzing skin conditions, Neural Regression for identifying and analyzing dengue infected risk area, Ridge regression and Decision tree classifier for analyzing blood report and severity identification. These were the most appropriate models in identifying complex patterns with large number of inputs and to provide accurate results.

The application can be improved for higher performances with more utilization of system requirements. The application features can be enhanced by allowing users to upload videos, doctor prescriptions, etc. Further testing and large-scale implementations of the mobile application can achieve to verify the system performance with thousands of user accesses. And also, system validation and improvements can perform with user feedbacks and surveys.

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