ARTIFICIAL INTELLIGENCE BASED DIAGNOSTIC SCREENING FOR DENGUE FEVER

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1. Introduction

Diagnostic screening is one of the most fundamental requirements in any medical treatment procedure. Most of the diagnostic screening processes rely heavily on expensive laboratory equipment and trained professional who operate the machinery. Diagnostic screening processes are generally invasive and it may take more than a day for results to come back from laboratory. Under normal medical conditions we have the flexibility and resources to take each patient's medical tests which help the doctor in diagnosing the patient's condition. However, in the case of an epidemic breakout or a resource constrained settings, it is not possible to have the results of every patient tested in a medical laboratory. This makes our project an ideal solution for this condition; as we will be providing a near real-time diagnosis of the patient based on his/her vital signs. To achieve the desired goal of the project, non-invasive techniques are used to collect physiological, clinical, and laboratory parameters of the infected subjects. The acquired data is fed in to an Artificial Intelligence powered device which is accompanied by an Android application, providing an easy-to-interact interface for both the doctors and the patients.

2. Objectives

1. To develop a non-invasive system for the acquisition of parameters on an easy-to-use, cost-effective diagnostic device that can swiftly and accurately measure vital health parameters and perform on-time screening for dengue fever detection.

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2. To develop an Android Application where the user logs in and enters and views their medical parameters (both clinical and physiological). The AI-powered expert system will take in the clinical and laboratory parameters of a patient and determine whether the patient has dengue fever or not.

3. Methods

We designed non-invasive artificial intelligent system for the acquisition of several clinical and laboratory parameters to perform on-time screening for dengue fever detection. Following physiological, clinical, and laboratory parameters were considered after consultation with medical experts and in line with the literature review under the AI powered research for dengue fever detection [1], [2], [3]:

| Physiological | Clinical | Laboratory |
|-------------------|---|---|
| Gender Weight | Petechial Rash Conjuctivity Gastric Pain Abdominal Pain Chill Bleeding Headache Vomit Macular | Hematocrit (HCT) Respiratory rate Pulse Rate Pulse Pressure Temperature Extracellular water (ECW) Intracellular water (ICW) Blood Oxygen level (SPO₂) |

Due to limited availability of real patients' data, synthetic data for laboratory parameters was generated after confirming the ranges by visiting doctors. Total data entries generated synthetically were 12,000 in number. To acquire clinical parameters, an AI powered medical chatbot has been designed which effectively interacts with the patients to obtain the clinical symptoms. The medical chatbot has been developed and trained using API.AI from where the access token for the bot has been embedded in the Android application to provide a user interface with runtime answering bot. An interface of the bot is shown in Figure 3.1.



Figure 3.1 Medical Chatbot Interface

After acquiring the clinical, laboratory, and physiological parameters of the subject, we implemented and trained two classifiers: Multivariate Logistic Regression and Support Vector Machines (SVMs). For testing purposes, real data was acquired from Military Hospital and Holy Family Hospital, during the dengue breakout in 2019. The real data acquisition is shown in Figure 3.2, 3.3, 3.4, and 3.5.



Figure 3.2 Data Acquisition at Holy Family Hospital, Rawalpindi



Figure 3.3 Data Acquisition at Military Hospital, Rawalpindi

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Figure 3.5 Data Acquisition Interface

The front view of the device used to acquire the laboratory parameters is shown in Figure 3.6.



Figure 3.6 Front view of the device

We acquired the available clinical and laboratory parameters of twenty-five patients suffering from dengue. The control data (twenty subjects) was obtained from within the university. Figure 3.7 shows a glimpse of the raw tabulated clinical and laboratory data that we acquired:

| Patient | SPO2 | RR | HR | HCT | Pulse_pressure | Chill | Bleeding | Anorexia | Headache | Nausea | Vomit | BodyAche | decision |
|---------|---------|--------|-----|-------|----------------|-------|----------|----------|----------|--------|-------|----------|----------|
| 7 | 0.95135 | 36.606 | 82 | 0.347 | 40 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 9 | 0.95137 | 24.193 | 98 | 0.321 | 90 | 1 | 1 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 10 | 0.95138 | 31.333 | 92 | 0.465 | 40 | 1 | 1 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 11 | 0.95114 | 20.667 | 89 | 0.473 | 40 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 |
| 12 | 0.95116 | 16.81 | 84 | 0.468 | 50 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 13 | 0.95141 | 27.778 | 92 | 0.384 | 40 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 14 | 0.95072 | 40 | 89 | 0.424 | 40 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 15 | 0.95115 | 32.308 | 87 | 0.495 | 40 | 1 | 0 | 1 | 1 | 0 | 1 | . 1 | 1 |
| 16 | 0.95143 | 12.916 | 95 | 0.452 | 40 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 17 | 0.95073 | 14.354 | 100 | 0.435 | 50 | 1 | 1 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 18 | 0.95137 | 23.939 | 85 | 0.411 | 40 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 19 | 0.95138 | 31.429 | 96 | 0.466 | 30 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |
| 20 | 0.95139 | 31.111 | 85 | 0.395 | 30 | 1 | 0 | 1 | 1 | 1 | 1 | . 1 | 1 |

Figure 3.7 Tabulated Data obtained from MH and HF Hospitals

4. Results

The obtained data was pre-processed and successful test was conducted under the recent data in field conditions. By using *Radial Basis Function (RBF)* as kernel, the accuracy obtained on the test data was 88% as shown in Figure 4.1.

| Predicted True | 0: Normal / Healthy | 1: Infected by Dengue | Class Precision |
|--------------------------|------------------------|--------------------------|-----------------|
| 0: Normal/Healthy | 18 | 2 | 86% |
| 1: Infected by Dengue | 3 | 18 | 90% |
| Class Recall | 90% | 86% | |

Figure 4.1 Results obtained using RBF kernel

5. Conclusion

There are several indicators of the dengue fever and transferring those symptoms, comprising of laboratory and clinical parameters, on an AI powered system can help in early diagnosis which can further assist in the outbreak forecasts. Our proposed solution is currently undergoing clinical trials with the collaboration of Military Hospital Rawalpindi. Its accuracy can be further improved by using a larger dataset and combining various machine learning techniques.

6. References

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