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Comparative Study of Prediction of IDBP values for Hemodialysis using Deep Learning

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Abstract: The field of medicine is expanding rapidly as new diseases appear regularly, necessitating the development of appropriate treatment options. A precise and efficient method of operation is necessary for correct diagnosis and treatment. Blood pressure (BP) is a vital sign that provides basic information about patients' health. During the clinical operation of hemodialysis, blood pressure (BP) variability affects significant global risks and secondary complications associated with adverse mortality. In patients with hypertension, continuous BP monitoring is important. If the scheme is automated, it can be very useful. Consequently, the implementation of an effective automatic medical diagnostic scheme could be very beneficial for all stratifications involved in this process.

Keywords: Prediction of IDBP Values for Hemodialysis, BP data, Deep Learning, Dense Layer CNN.

I. INTRODUCTION

Intradialytic hypotension (IDH), which occurs in 15% to 20% of therapies for HD patients, is a frequent and difficult consequence. IDH has been linked to numerous health hazards, such as coronary artery disease, heart attacks, and overall mortality. Although a number of high danger traits also comorbidities have regularly been noted, it is still challenging to forecast the likelihood of cardiovascular death. In earlier investigations, machine learning techniques were employed to create binary decision models that attempted to predict whether or not patients had IDH. However, these models failed to consider the data set's complicated time series properties, such as background patient data and blood pressure.

II. LITERATURE SURVEY

One of the important signs provides the patient with basic health information is blood pressure (BP). Blood flow from the beating heart puts pressure on the blood vessels. Systolic blood pressure (SBP) is an increase in pressure brought on by the heart's systolic contraction, while diastolic blood pressure (DBP) is the low pressure in between SBPs. Due to its association with a number of disorders, including arrhythmia, heart attacks, blindness, and brain stroke, high blood pressure, or hypertension, is referred to as a "silent killer". Worldwide, hypertension is thought to affect 1.13 billion individuals. A sphygmomanometer, which is typically used in a doctor's office, is the gold standard of blood pressure monitoring. However, taking your blood pressure in a medical setting could be.

III. PROPOSED WORK

We required the model to forget the less important information and recall the important information in order to maintain a sufficient degree of accuracy with constrained time and space resources for BP data that is highly time-related. The most conventional kind of deep learning model is the CNN. As a result, the CNN model was initially employed in the study to intercept the reliable and abstract data. This procedure may assist preserve or extract additional features, and the output of CNN for temporal characteristics that are already present for time series prediction The suggested technology estimates the patient's blood pressure using 15 months' worth of medical information.

IV. METHODOLOGIES

In our project we are using 3 modules Admin, Doctor, Patient. In admin module admin can login through the valid email id and then admin can add both Doctors as well as hospitals. Also admin can view the details of Doctor, Patient and Hospitals. In Doctor module doctor must login through their valid email id and password and in the home page of the doctor, doctor can add patient and their details also they can view their details and they can view their own profile. In patient module patient must login through email id and password in their login page and in the home page of a patient where the individual can view their predicted BP values.

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A. Deep Learning

Artificial intelligence (AI) and machine learning techniques called deep learning model how people acquire specific types of information. Deep learning makes this process quicker and simpler, which is very advantageous to data scientists who are entrusted with gathering, analysing, and interpreting massive volumes of data. Deep learning may be conceptualised as an automated kind of predictive analytics at its most basic. Deep learning algorithms are piled in a hierarchy with progressively higher levels of complexity and abstraction than conventional machine learning algorithms, which are linear.

- B. Convolution Neural Network
- 1) Step-1: Import key libraries.
- 2) Step-2: Reshape the data.
- 3) Step-3: Normalize the data.
- 4) Step-4: Define the model function.
- 5) Step-5: Run the model.

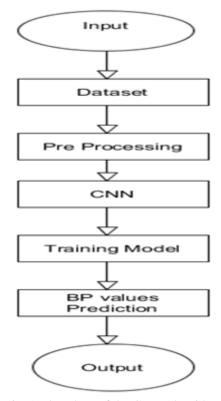


Fig. 1 Flowchart of the CNN Algorithm

C. Dataset

To put it simply, a dataset in machine learning is a group of data points that a computer can analyse and forecast as a single entity. To a computer who doesn't see data the same way that people do, this means that the data collected should be uniform and intelligible. From March 2020 to May 2021, we compiled a database including information on fifteen-month therapy sessions. In order to fine-tune the model's performance in terms of quality and accuracy for this study, the dataset was then under sampled to contain records that allow time period values within the bounds of 0 to 200. Additionally, during the data gathering phase, we trimmed records that lacked valid access, omitted records with fewer than 200 time periods per patient, and any other inadequate HD sessions.

D. System Architecture

In this project we are using blood pressure .After collecting datasets they are passed to the data Pre-processing unit in which the datasets are splits for training and testing each. After that frequencies are passed through the bandpass filtering. We make use CNN algorithm for classifications and test the valid datasets, using this algorithms we are build the model.

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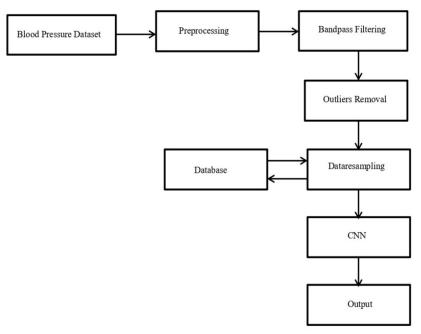


Fig. 2 System Architecture

V. RESULT ANALYSIS

In the below figure Fig 3 shows the Vs True BP Values Vs Predicted BP Values. A sample of each patient will be collected in the amounts of 0, 20, 40, 60, 80, and 100. The patient's True Blood Pressure is displayed on the Blue line, while their Predicted Blood Pressure is displayed on the Red line. BP readings are 60, 80, 100, 120, 140, 160, and 180. The patient's True BP Values vs. Predicted BP Values are displayed in this result.

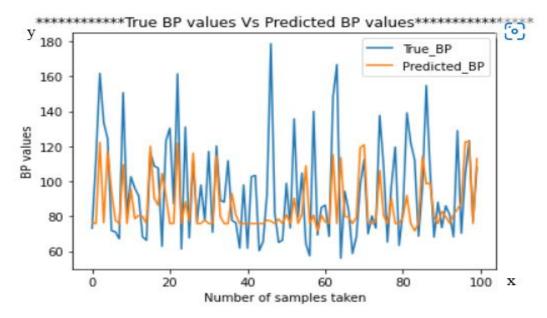


Fig. 3 Prediction of True BP Values Vs Predicted BP Values

In the below Figure Fig. 4 shows the Blood Prediction Value of hemodialysis patient. the Blood Pressure Graph on the left of the graph represents the actual signal value 70, 80, 90, 100, 110, 120 on the horizontal y axis, and the sample size 0, 20, 40, 60, 80, 100, 120 is on the vertical x axis. The line goes through all points in the graph .As such, the closer a plotted point is to the diagonal line, the more accurate the prediction.

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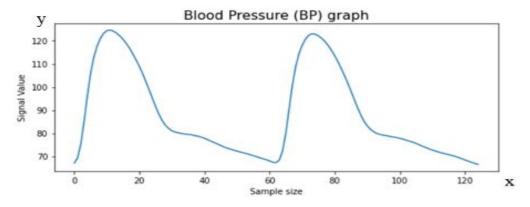


Fig. 4 Blood Pressure Graph

In the figure Fig. 5 shows the PPG Graph of hemodialysis patient. A continuous, non-invasive method of estimating blood pressure that may be included into wearable technology has recently been presented as photoplethysmography (PPG). The arterial pressure pulse is connected to the volumetric pulsations of blood in tissue, which are recorded by PPG.

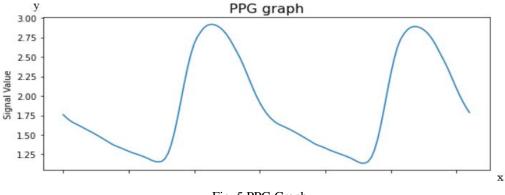


Fig. 5 PPG Graph

In the figure Fig. 6 shows the ECG Graph of hemodialysis patient. The normal ECG pattern will be produced if the heart is pumping steadily: The electrical impulse (excitation) spreads throughout the two atria of the heart as shown by the first peak (P wave). Blood is pumped into the ventricles as the atria contract (squeeze) before instantly relaxing. The ventricles are then reached by the electrical impulse. The signal value, also known waves of the ECG. In ECG The examination is painless and only lasts a few minutes. The heart's electrical activity causes the heart muscles to contract, which causes the heart to pump. The ECG consists of waves, or spikes and troughs. The wave pattern aids in determining our heartbeat's rhythm and pace.

In the Fig 7 it defines the predicted BP values of a patient that shown in a graph using with the sample values.

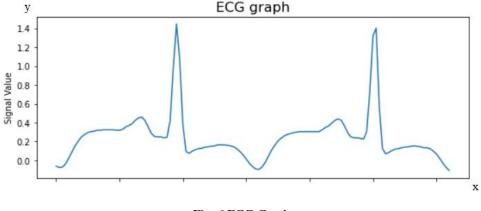


Fig. 6 ECG Graph



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Fig. 7 Blood Pressure Value Prediction

Epochs are the total number of cycles used to train the machine learning model using all of the training data. All training data is utilised precisely once in Epoch. The total number of trips an algorithm has made around the training dataset is another way to think of epoch, or the time between two events. In training, a pass was considered to be one pass if it was both forward and backward. A machine learning model typically needs a small number of Epochs to be trained. Iteration and an epoch are typically used synonymously. How many times you go through your training set is indicated by the number of epochs. Since the model is changed each time a batch is processed, it may be modified more than once in a single epoch. The model is updated once every epoch if batch size is set to the length of x.

Epoch	Time	Loss	Mean_absolute_error
1	149s 18ms/step	21.8080	22.3027
2	147s 19ms/step	20.4367	22.9310
9	131s 17ms/step	19.7415	20.2356
10	133s 17ms/step	19.7033	20.1974

Table 1 Epoch Iteration

VI. CONCLUSIONS

Therefore, we use our acquired time-sequence dataset to benchmark the accuracy of our model for this specific temporal sequential prediction for blood pressure value, on which not a lot of work has been done. We leverage CNN-GRU and use almost 100,000 valid records. Had higher results across the board when compared to earlier tests using CNN-GRU for value prediction. Verifying that this model is multi-featured and has time-series data characteristics gives a lot of benefits. However, if we add more records from different types of wearable devices and event-specific data from physiological data, more study is required to add the parameters. In keeping with this, we'll also search for an improved model with greater hyperparameter customization in the future.

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