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Learning to Predict: Integration with Domain Knowledge for Intracranial Pressure Prediction using Autoencoder Decoder Algorithm

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ABSTRACT Precise management of patients with cerebral diseases often requires intracranial pressure (ICP) monitoring, which is highly invasive and requires a specialized ICU setting. The ability to noninvasively estimate ICP is highly compelling as an alternative to, or screening for, invasive ICP measurement. Most existing approaches for non-invasive ICP estimation aim to build a regression function that maps non-invasive measurements to an ICP estimate using statistical learning techniques. These data-based approaches have met limited success, likely because the amount of training data needed is onerous for this complex applications. Intracranial pressure (ICP) normally ranges from 5 to 15 mmHg. Elevation in ICP is an important clinical indicator of neurological injury, and ICP is therefore monitored routinely in several neurological conditions to guide diagnosis and treatment decisions. Current measurement modalities for ICP monitoring are highly invasive, largely limiting the measurement to critically ill patients. An accurate non-invasive method to estimate ICP would dramatically expand the pool of patients that could benefit from this cranial vital sign. Methods: This article presents a spectral approach to model based ICP estimation from arterial blood pressure (ABP) and cerebral blood flow velocity (CBFV) measurements. The model captures the relationship between the ABP, CBFV, and ICP waveforms and utilizes a second-order model of the cerebral vasculature to estimate. In this work, we discuss an alternative strategy that aims to better utilize non-invasive measurement data by leveraging mechanistic understanding of physiology. Specifically, we developed a CNN framework that combines a multiscale model of intracranial physiology with non-invasive measurements of cerebral blood flow using transcranial Doppler. Virtual experiments with synthetic data are conducted to verify and analyze the proposed framework. A preliminary clinical application study on two patients is also performed in which we demonstrate the ability of this method to improve ICP prediction.

Keywords: Convolutional Neural Network (CNN), Deep Learning (DL), Neural Networks (NN),
Random forest classifier

I. INTRODUCTION

Despite tremendous advancements in the healthcare sector, cardiovascular diseases (CVDs) still secure the top positions last year in the list of leading causes of death globally. The most fatal CVD is the Ischaemic Heart Disease which is termed by the World Health Organization (WHO) as the Worlds Biggest Killer as it accounted for 16% of the total deaths from 2000 to 2019. The second, third, and fourth positions are secured by Stroke, Chronic Pulmonary Diseases and Lower Respiratory Infections, respectively which are also, directly and indirectly, related to CVDs [2-4]. Hypertension or High Blood Pressure (BP) is one of the leading causes of CVDs: almost 54% of strokes and 47% of coronary heart diseases, worldwide, can be attributed to high BP . In the USA alone, there are around 67 million people (almost one-third of the population) suffering from various hypertension problems while the irony is, according to this statistic , more than half of them are reluctant to mitigate their condition. The main reason behind this kind of reluctance seen among high BP patients is the dormant nature of hypertension which eventually leads to untimely death. For this reason, it is commonly termed the Silent Killer. Due to the silent nature of hypertension, it is crucial to continuously monitor the BP of the patients. Due to a shortage of expert physicians compared to the huge number of patients; automated BP monitoring methods seem to be a viable alternative in this regard.

Hypertension, defined as systolic blood pressure (SBP) larger than 140mmHg or diastolic blood pressure (DBP) larger than 90mmHg1 , is estimated to have caused 9.4 million annual deaths globally, 17% of the total death in 2012 and 7% of total disability-adjusted life years (DALYs) . If left uncontrolled, hypertension causes stroke, myocardial infarction (MI), cardiac failure, dementia, renal failure, and even blindness. In adults, hypertension after diabetes is the second reason to increase the risk of cardiovascular disease (CVD) and several types of cancer, as well as multiple nonfatal diseases. Hypertension has been increasing in recent years. By 2030, 40.5% of the US population is projected to have some form of CVD . While people with the risk of hypertension need to measure their blood pressure frequently, conventional cuff-based BP measurement devices are expensive and inconvenient for continuous monitoring. Thus the development of alternative methods is necessary.

Intracranial Pressure (IP) commonly measured in mmHg is a quasi-periodic signal in sync with an individuals heartbeats. The upper peak in each period is called the Systolic Intracranial Pressure or SIP, and the lower bound in each period is called Diastolic Intracranial Pressure or DIP. While Intracranial pressure is difficult to monitor continuously in a non-clinical setting, Photoplethysmography (PPG) is a non-invasive optical method that measures a related signal: Intracranial volume temporal variations in the vessels and tissues. PPG signals are obtained from pulse oximeters, emitting visible light (LED) on the skin and measuring the micro-variations in the transmitted, or reflected light intensity (photo-diode). PPG sensors are small in size and low cost to build, and they already exist in most newer wearables (e.g. smartwatches, activity trackers, and smart rings).

In recent years, there has been an extensive body of research studying similarities and correlation of PPG signals and Aortic Pressure waveforms, as well as the possibility of estimating SBP and DBP based on PPG signals. Since both signals are originating from the same source (the individuals heartbeats), they are highly correlated. However, since Aortic and PPG are generally measured from different parts of the body (e.g. arm and wrist) using different devices, they are typically out of phase. Figure 1 is based on experimental data after time-shift alignment (since PPG signal does not have a unit, in the figure it is scaled for easier readability). Some methods such as the one in are proposed to automatically detect and compensate for this phase difference.

Injuries to and disorders of the brain such as traumatic brain injury (TBI), hemorrhagic stroke, hydrocephalus, or brain tumor are responsible for a significant fraction of the total hospital visits in the United States each year. These conditions have in common that one of the intracranial compartments (brain tissue, cerebrospinal fluid (CSF), or blood) expands at the expense of the volumes occupied by the other two, owing to the volume constraint imposed by the rigid skull and relatively inelastic dura mater. This restriction in volume implies that uncompensated shifts and expansions in compartmental volumes lead to an increase in the compartment pressure. Hence, the diagnosis, monitoring and treatment of patients with the conditions often rely on the measurement and tracking of intracranial pressure (ICP), as elevations in ICP are correlated with poor outcome in brain injury patients. Such elevations need to be detected and managed expeditiously as they can result in poor perfusion of the brain tissue and may lead to brain herniation.

Normal mean ICP values range from 5 to 15 mmHg. In standard clinical practice, ICP is monitored invasively by placing a fluid filled catheter into the ventricular CSF space and, by convention, levelling the pressure transducer to the Foramen of Monro. Alternatively, a pressure-sensitive probe can be placed into the brain tissue to measure tissue pressure. Both approaches are used for decision making in current clinical practice.

The invasiveness of the ICP measurement and the need for neurosurgical expertise to place such a catheter have motivated a variety of engineering approaches to make this important cranial vital sign available noninvasively. A particular class of approaches to continuous ICP estimation relies on waveform measurements of cerebral blood flow velocity (CBFV), recorded noninvasively using transcranial Doppler (TCD) ultrasonography, and radial arterial blood pressure (ABP), measured invasively through indwelling catheters. While these methods use invasively measured ABP, the invasiveness of placing a radial artery line and the associated risk for tissue damage and infection are considerably lower than those associated with placing a ventricular catheter for ICP measurement. Hence the usage of the term non-invasive for ICP estimation based on simultaneously acquired (non-invasive) CBFV measurements and (invasive) ABP measurements has become established in the field.

Intracranial pressure (ICP) monitoring is common practice in the acute phase of severe head trauma, hemorrhagic stroke, and hydrocephalus, to alert care providers to elevated levels of ICP and the associated risk of secondary brain injury and the possibility of brain herniation . While care guidelines base treatment recommendations on the mean level of ICP the ICP waveform exhibits characteristic intra-beat pulsations (Fig. 1), varies with the respiratory cycle, and also shows low-wave oscillations in the 0.3 to 3 cycles/min range. Analysis of these different waveform components has been explored for diagnostic and prognostic purposes.

Within a cardiac beat, up to five peaks, termed P1 to P5, have been reported , and a significant body of work has focused on mining such intra-beat morphological features for improved clinical decision making . Such research has addressed the question of whether analysis of the ICP waveform morphology can aid in assessing the elastance of the intracranial space. A high intracranial elastance (ICE) indicates a potentially dangerous state in which a small increase in one of the intracranial compartment volumes causes a dramatic increase in ICP. Cardoso et al. suggested that the ratio between the P2 and P1 amplitude (the P2-to-P1 ratio) is a quantifying measure of the ICE, with a ratio greater than unity indicating a compromised ICE. Szewczykowski et al. analyzed the ICP (peak-to-peak) pulse amplitude as a function of mean ICP to assess ICE, and Czosnyka et al. introduced the RAP index as the correlation coefficient between the ICP pulse amplitude and the mean ICP.

Another line of investigation has focused on whether cerebral blood flow (CBF) autoregulation can be assessed through analysis of the slow-wave components of the ICP signal. In patients with severe traumatic brain injury, the cerebral vasculature’s ability to regulate its own blood supply is thought to be impaired or entirely lost, thus putting the patients at significant risk of further injury if a mismatch occurs between the brains metabolic substrate requirements and the systemic supply. To this end, the Pressure Reactivity Index (PRx) is a dynamic indicator of pressure autoregulation that has attracted significant attention in the last two decades. The PRx is based on the cerebrovascular vasomotor response to slow variations of ABP, that can be observed in the ICP signals low frequency (LF) range between 0.02 to 0.065 Hz, and is calculated as the correlation coefficient between low-frequency variations in arterial blood pressure and ICP.

II.RELATED WORK

Intracranial pressure (ICP) monitoring is common practice in the acute phase of severe head trauma, hemorrhagic stroke, and hydrocephalus, to alert care providers to elevated levels of ICP and the associated risk of secondary brain injury and the possibility of brain herniation . While care guidelines base treatment recommendations on the mean level of ICP the ICP waveform exhibits characteristic intra-beat pulsations (Fig. 1), varies with the respiratory cycle, and also shows low-wave oscillations in the 0.3 to 3 cycles/min range. In Health Data Driven on Continuous Blood Pressure Prediction Based on Gradient Boosting Decision Tree Algorithm. Diseases related to issues with blood pressure are becoming a major threat to human health. With the development of telemedicine monitoring applications, a growing number of corresponding devices are being marketed, such as the use of remote monitoring for the purposes of increasing the autonomy of the elderly and thus encouraging a healthier and longer health span.

Using machine learning algorithms to measure blood pressure at a continuous rate is a feasible way to provide models and analysis for telemedicine monitoring data and predicting blood pressure. For this paper, we applied the gradient boosting decision tree (GBDT) while predicting blood pressure rates based on the human physiological data collected by the EIMO device. EIMO equipmentspecific signal acquisition includes ECG and PPG. In order to avoid over-fitting, the optimal parameters are selected via the cross-validation method. Consequently, our method has displayed a higher accuracy rate and better performance in calculating the mean absolute error evaluation index than methods, such as the traditional least squares method, ridge regression, lasso regression, ElasticNet, SVR, and KNN algorithm. When predicting the blood pressure of a single individual, calculating the systolic pressure displays an accuracy rate of above 70% and above 64% for calculating the diastolic pressure with GBDT, with the prediction time being less than 0.1 s. In conclusion, applying the GBDT is the best method for predicting the blood pressure of multiple individuals: with the inclusion of data such as age, body fat, ratio, and height, algorithm accuracy improves, which in turn indicates that the inclusion of new features aids prediction performance. For the endings outlined in this paper, the EIMO device is used to collect the physiological data from the human body, alongside technological devices such as the Wrist Blood Pressure Monitor and Suntech,which focused on collecting blood pressure values. GBDT algorithm was them employed to provide analysis and modeling for the data, predicting blood pressure rates in the process. The nonlinear function was created and tested its reliability for the determination of absolute SBP (Systalic Blood Pressure).[1]

The regulation of Mean Arterial Pressure (MAP) through the infusion of Sodium Nitroprusside (SNP). is optimized by the use of PIDNN Multi-layer Perception (MLP) is used as Neural Network pattern predictor[2]. In terms of evaluating the performance quality of the GBDT algorithm, this was tested against the traditional LS, RR, SVR, Elastic Net, KNN and Lasso.

In this work, authors consider three mathematical models that relate pulse wave velocity (PWV) with arterial stiffness.[3] While one model considers blood to be a nonviscous and incompressible fluid, the other considers it to be a viscous and compressible. Pulse transit time has been measured experimentally for five different individuals of different ages and heights from where PWV has been estimated.

An automated ICP level prediction model based on machine learning method is proposed in this paper. Multiple features, including midline shift, intracranial air cavities, ventricle size, texture patterns, and blood amount, are selected, extracted and aggregated using different methods.[4]

This paper proposes a machine learning method to predict the systolic blood pressure (SBP) of a person using the backpropagation (BP) neural network and the radial basis function (RBF) network. The average prediction errors (absolute difference between the predicted value and measured value) for the relationship between SBP and input attributes (BMI, age, exercise and stress level) are at an acceptable level. The results obtained from the BP neural network and RBF network are in agreement. Generally speaking, with the database used in the experiment, the use of 80% of data for training, and use of four or five hidden nodes in both neural networks, are giving reasonably good result[5]

Abnormal elevation of intracranial pressure (ICP) can cause dangerous or even fatal outcomes. The early detection of high intracranial pressure events can be crucial in saving lives in an intensive care unit (ICU). Despite many applications of machine learning (ML) techniques related to clinical diagnosis, ML applications for continuousICP detection or short-term predictions have been rarely reported. This study proposes an efcient method of applying an articial recurrent neural network on the early prediction of ICP evaluation continuously for TBI patients.

After ICP data pre-processing, the learning model is generated for thirteen patients to continuously predict the ICP signal occurrence and classify events for the upcoming 10 minutes by inputting the previous 20-minutes of the ICP signal. As the overall model performance, the average accuracy is 94.62%, the average sensitivity is 74.91%, the average specificity is 94.83%, and the average root mean square error is approximately 2.18 mmHg. This research addresses a significant clinical problem with the management of traumatic brain injury patients. The machine learning model data enables early prediction of ICP continuously in a real-time fashion, which is crucial for appropriate clinical interventions.

III. SYSTEM MODEL

Exploratory Data Analysis Exploratory Data Analysis (EDA) is an approach to analyzing data. Its where the researcher takes a birds eye view of the data and tries to make some sense of it. Its often the first step in data analysis, implemented before any formal statistical techniques are applied. Exploratory Data Analysis (EDA) is a powerful approach to analyze data sets using summary statistics and graphical tools to gain insight into the data. EDA helps to find anomalies like outliers or unusual observations in the data. It helps to identify patterns, understand possible relationships between variables, and generate interesting hypotheses using statistical methods. EDA is also helpful in cleaning data and representing the data graphically

A.ARCHITECTURE.

Fig .1. shows that the System Architercture .Initially data is collected and analyzed to represent the data graphically.

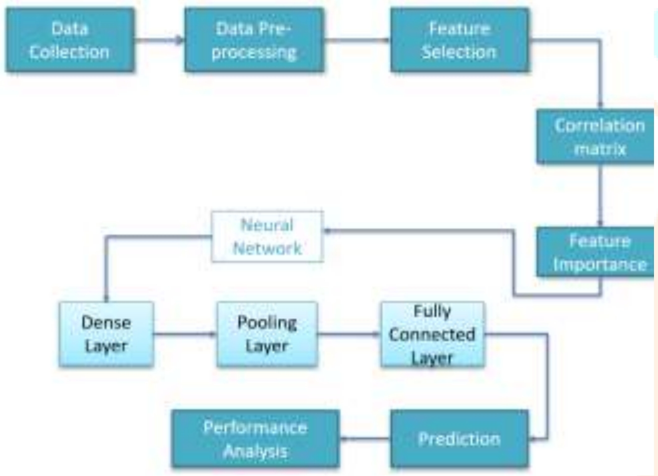


Fig.1.System Architecture

The encoder and decoder is used for preprocessing the data. The datasets are further divided into Test, Training and Validation data. Convolutional neural networks (CNN) extract information based not only on a single sample but also on the samples neighborhood, which allows them to easily extract morphological features. After extracting the important features, this features are used for training the model with the given datasets. The model is trained with 80% of data and remaining data is used for testing the data. Testing and Validation is done. Then the accuracy of model prediction is calculated.

B.DATA PREPROCESSING

UNet architecture can be broadly thought of as an encoder network followed by a decoder network. The encoder is the first half in the architecture diagram. The decoder is the second half of the architecture. It consists of four encoder blocks and four decoder blocks that are connected via a bridge. The encoder network (contracting path) half the spatial dimensions and double the number of filters (feature channels) at each encoder block. Likewise, the decoder network doubles the spatial dimensions and half the number of feature channels. The encoder network acts as the feature extractor and learns an abstract representation of the input image through a sequence of the encoder blocks. Each encoder block consists of two 3x3 convolutions, where each convolution is followed by a ReLU (Rectified Linear Unit) activation function. The ReLU activation function introduces non-linearity into the network, which helps in the better generalization of the training data. The output of the ReLU acts as a skip connection for the corresponding decoder block. Next, follows a 2x2 max-pooling, where the spatial dimensions (height and width) of the feature maps are reduced by half. This reduces the computational cost by decreasing the number of trainable parameters.

C. MODEL TRAINING

Keras models can be used to detect trends and make predictions, using the model.predict() class and its variant, reconstructed_model.predict(). A final model can be saved, and then loaded again and reconstructed. The reconstructed model has already been compiled and has retained the optimizer state, so that training can resume with either historical or new data

Keras Model Components

Architecture/Configuration: Specifies what layers the model contains, and how they are connected.

Weights: Input parameters that influence output in a Keras model.

Optimizer: Optimizer/loss function used to minimize loss. Usage: One of two arguments required for compiling a Keras model

Set of Losses and Metrics: When a model is compiled, compile() includes required losses and metrics.

D. CONFUSION MATRIX

This method is used in the outline of AI group execution. Calculating the chaotic grid makes it easier for us to understand the correctness of the representation model and the types of errors it causes. It is used to calculate the accuracy of the representation, just like arranging true and prescient marks. They graphically display the classifier and its representation. The confusion matrix denotes the overall number of actual and predicted labels for a particular algorithm. Similarly, the disordered dot matrix deals with the absolute number of actual marks and the expected names for arrangement. These real and expected names are a mixture of true positives, true negatives, false positives, and false negatives. Through these qualities, we will determine the accuracy of our model arrangements and expectations.

TN solves the true negative: it is all the advantages of the precise anticipation of a negative case.

FP resolves false positives: it is the sum of deviations from the basic expectations that have occurred as a positive.

FN solves the false negatives: it is the sum of deviations from the basic expectations that appear negative.

TP solves True-Positive: it is the sum of the exact expectation that an event is positive.

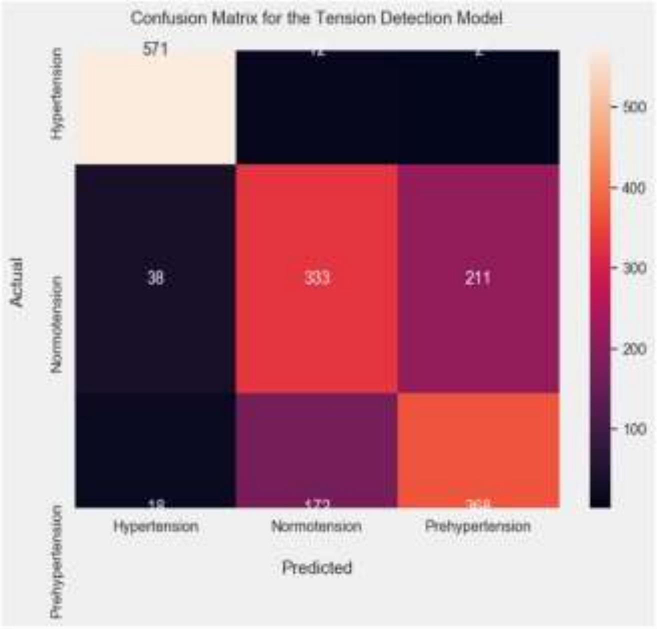


Fig.2. Confusion matrix for tension Detection

The detection of the tension with the data collected is shown in fig.2. The prediction is checked whether correct or not. The model is trained and then tested to get the result and prediction.

Algorithms:

Auto Encoder Decoder Algorithm: Autoencoders are a type of deep learning algorithm that are designed to receive an input and transform it into a different representation. They play an important part in image construction. An Autoencoder consists of three layers: 1.Encoder, 2.Code , 3.Decoder

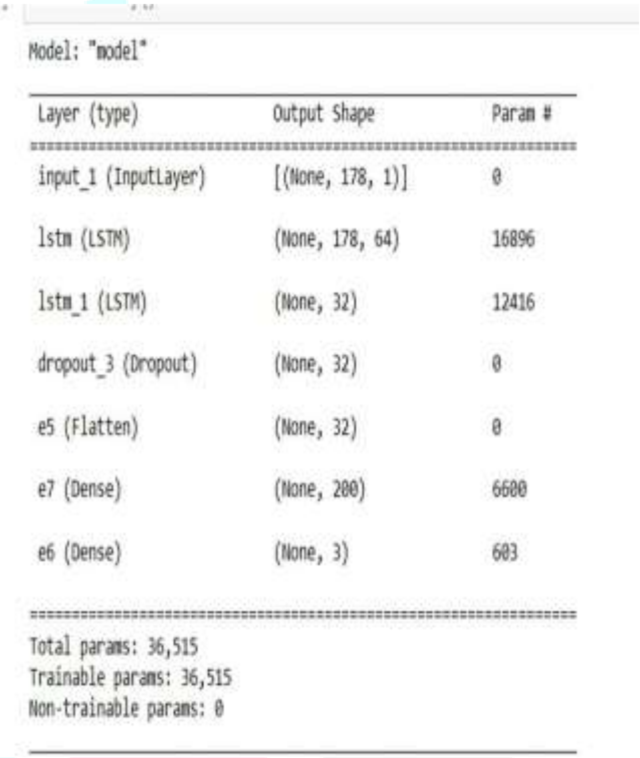
The Encoder layer compresses the input image into a latent space representation. It encodes the input image as a compressed representation in a reduced dimension. The code layer represents the compressed input fed in to the decoder layer. The decoder layer decodes the encoded image back to the original dimension. The decoded image is reconstructed from latent space representation, and it is reconstructed from the latent space representation and is a lossy reconstruction of the original message.

Random Forest:

Random Forest is one of the most popular and commonly used algorithms by Data Scientists. Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression.

LSTM Algorithm:

LSTM stands for long short-term memory networks used in the field of Deep Learning. It is a variety of recurrent neural (RNNs) that are capable of learning networks, used in the field of Deep) that are capable of learning long-term dependencies, especially in sequence prediction problems. LSTM has feedback connections, i.e., it is capable of processing the entire sequence of data, apart from single data points such as images This finds application in speech recognition, translation, etc. LSTM is a special kind of RNN, which shows outstanding performance on a large variety of problems.



```
Model: "model"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
input_1 (InputLayer)        [(None, 178, 1)]          0

lstm (LSTM)                 (None, 178, 64)           16896

lstm_1 (LSTM)               (None, 32)                12416

dropout_3 (Dropout)         (None, 32)                0

e5 (Flatten)                (None, 32)                0

e7 (Dense)                  (None, 200)               6600

e6 (Dense)                  (None, 3)                 603

=================================================================
Total params: 36,515
Trainable params: 36,515
Non-trainable params: 0
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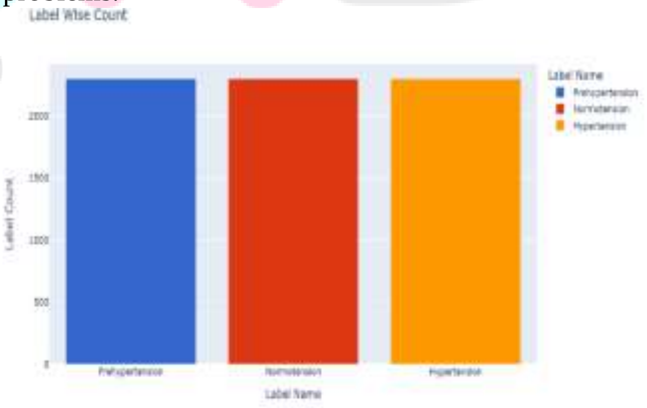

Fig.3. Label Wise Count

The Label wise count represents the Prehypertension, Normotension and Hypertension values shown in fig.3.This label wise count all are same for the prediction.

Exploratory Data Analysis (EDA) is one of the techniques used for extracting vital features and trends used by machine learning and deep learning models in Data Science. Exploratory data analysis (EDA) involves using graphics and visualizations to explore and analyze a data set. The goal is to explore, investigate and learn, as opposed to confirming statistical hypotheses. Test, Train and Validation Split All three datasets are further divided into Test, Training and Validation data. Test Data is a small chunk of data obtained randomly from the dataset, which occupies 3.5% of each dataset. Training Data is the 80% of the remaining data used for training the models. Validation Data is the 20% of the remaining data used for validating the classifier. The classifiers used this validation data to avoid overfitting and improve model performance. Convolutional neural networks (CNN) extract information based not only on a single sample but also on the samples neighborhood, which allows them to easily extract morphological features and therefore makes them a perfect fit for the task of morphological classification. Additionally, in this case, due to the relatively short duration of processed signals (mostly less than 1 s in length), the networks are not required to overcome the challenge of modelling the long term dependencies. ResNets are deep convolutional models that use residual connections between layers for more stable error propagation. The hyperparameters were chosen through the empirical choice method across many conducted experiments with each of the proposed models.

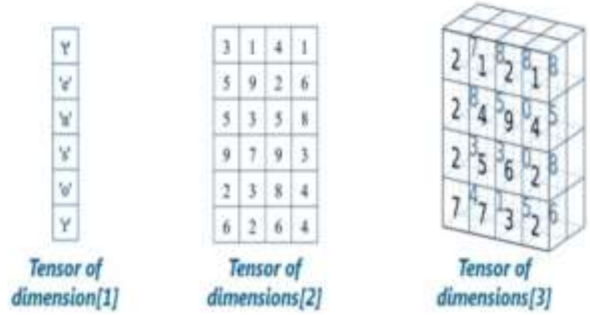

Fig.4. Tensor Flow

The Tensor Flow Diagram represents the data is kept in very tight in one place than performing all analysis around it is shown in fig.4.Tensor Flow works on Multidimensional data arrays.

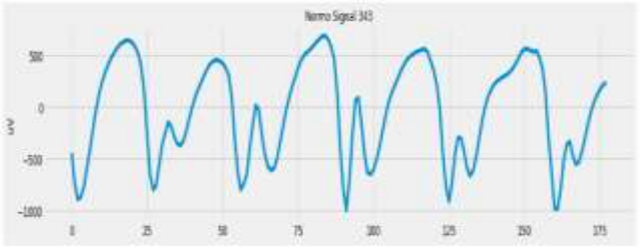

Fig.5. Tension Signal

The tension signal for the different tension are marked and one of the tension signal is shown in fig.5.

V. RESULTS AND DISCUSSION

Continuous nICP estimation can benefit a large number of patients that have traditionally been excluded from ICP monitoring due to the current invasiveness of the measurement. The nICP estimation framework proposed in this paper attempts to overcome challenges associated with model-based nICP estimation methods. Several possible time offsets between the rABP and CBFV are considered, which helps address the challenge posed by unknown (and patient-specific) time offsets between these signals. Estimation is performed within a Bayesian framework, which helps increase the methods resilience to structured errors that may be introduced, for instance, by differences between rABP and cABP morphology, and also to unstructured errors due to signal noise and motion artifacts in recorded data. Moreover, ICP pulse pressure amplitudes are determined in a patient-specific manner. It is hoped that this work will pave the way towards developing a reliable, continuous, realtime, accurate, and fully noninvasive ICP monitoring device to improve neurocritical care across the world.

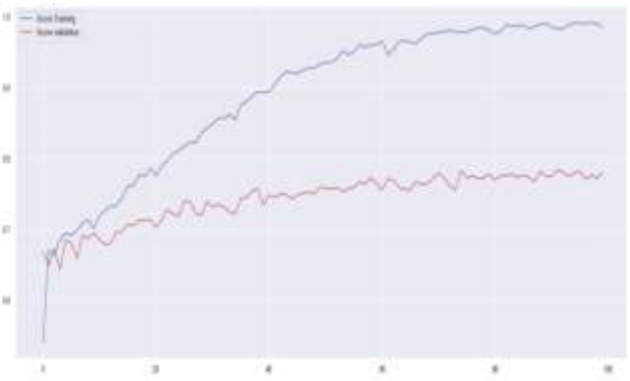

Fig. 6. Scores Plot

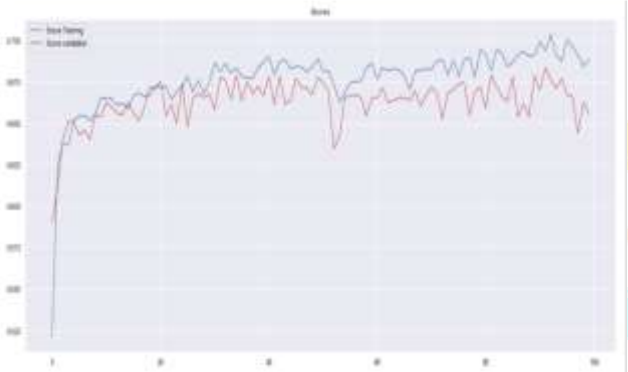

Fig.7. Scores History

The test Scores after the training is shown in fig.6. and fig.7.

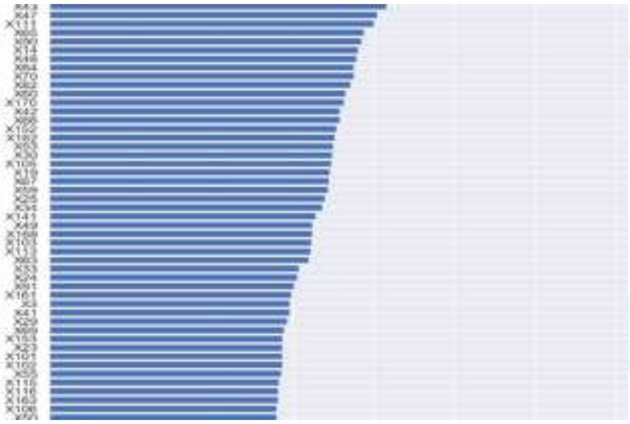

Fig.8. Random Forest output

The important Features is extracted by using the Random Forest and it is shown in fig.8.

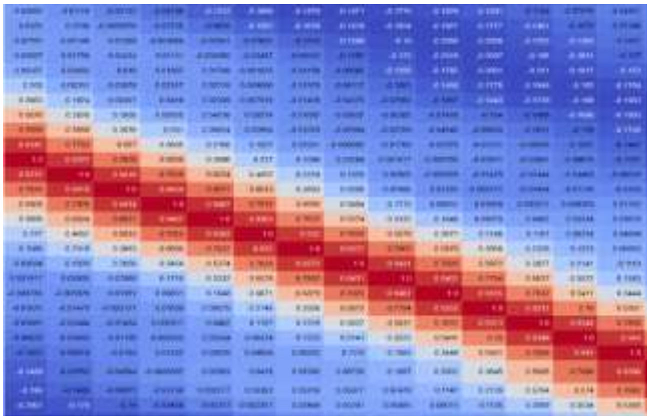

Fig.9. Co-Relation Matrix

The Co-relation matrix is used to differentiate the dataset values by different colours and it is shown in fig.9.

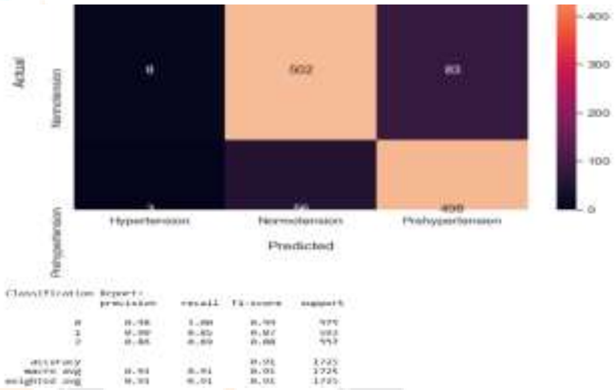

Fig.10. Prediction with Accuracy

The Final Prediction after training the model is shown in fig.10.

Intracranial pressure (ICP) monitoring is common practice in the acute phase of severe head trauma, hemorrhagic stroke, and hydrocephalus, to alert care providers to elevated levels of ICP and the associated risk of secondary brain injury and the possibility of brain herniation. While care guidelines base treatment recommendations on the mean level of ICP the ICP waveform exhibits characteristic intra-beat pulsations varies with the respiratory cycle, and also shows low-wave oscillations in the 0.3 to 3 cycles/min range. Analysis of these different waveform components has been explored for diagnostic and prognostic purposes.

Within a cardiac beat, up to five peaks, termed P1 to P5, have been reported, and a significant body of work has focused on mining such intra-beat morphological features for improved clinical decision making. Such research has addressed the question of whether analysis of the ICP waveform morphology can aid in assessing the elastance of the intracranial space. A high intracranial elastance (ICE) indicates a potentially dangerous state in which a small increase in one of the intracranial compartment volumes causes a dramatic increase in ICP. Cardoso et al. suggested that the ratio between the P2 and P1 amplitude (the P2-to-P1 ratio) is a quantifying measure of the ICE, with a ratio greater than unity indicating a compromised ICE. Szewczykowski et al. analyzed the ICP (peak-to-peak) pulse amplitude as a function of mean ICP to assess ICE, and Czosnyka et al. introduced the RAP index as the correlation coefficient between the ICP pulse amplitude and the mean ICP.

Another line of investigation has focused on whether cerebral blood flow (CBF) autoregulation can be assessed through analysis of the slow-wave components of the ICP signal. In patients with severe traumatic brain injury, the cerebral vasculatures ability to regulate its own blood supply is thought to be impaired or entirely lost, thus putting the patients at significant risk of further injury if a mismatch occurs between the brains metabolic substrate requirements and the systemic supply . To this end, the Pressure Reactivity Index (PRx) is a dynamic indicator of pressure autoregulation that has attracted significant attention in the last two decades. The PRx is based on the cerebrovascular vasomotor response to slow variations of ABP, that can be observed in the ICP signals low frequency (LF) range between 0.02 to 0.065 Hz, and is calculated as the correlation coefficient between low-frequency variations in arterial blood pressure and ICP.

VI. CONCLUSION

Continuous nICP estimation can benefit a large number of patients that have traditionally been excluded from ICP monitoring due to the current invasiveness of the measurement. The nICP estimation framework proposed in this paper attempts to overcome challenges associated with model-based nICP estimation methods. Several possible time offsets between the rABP and CBFV are considered, which helps address the challenge posed by unknown (and patient-specific) time offsets between these signals. Estimation is performed within a Bayesian framework, which helps increase the methods resilience to structured errors that may be introduced, for instance, by differences between rABP and cABP morphology, and also to unstructured errors due to signal noise and motion artifacts in recorded data. Moreover, ICP pulse pressure amplitudes are determined in a patient-specific manner. It is hoped that this work will pave the way towards developing a reliable, continuous, realtime, accurate, and fully noninvasive ICP monitoring device to improve neurocritical care across the world.

VII. FUTURE SCOPE

The present study suggests adopting values as potential indices for multimodal monitoring systems to quantify intracranial hypertensive episodes for its better management in TBI patients. A future study may be intended to comprehend the associated physiological processes such as cerebral auto-regulation and CSF, which play important role in ICP dynamics.

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