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# Monitoring Pressure in Controlled Ventilator System under Different Lung Settings

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**ABSTRACT**

To support the weak human lungs with supply of continuous airway pressure in respiratory system throughout the time when patient is on life-support is quite a daunting and people-driven job. To reduce the stress on few doctors and nurses of saving innumerable lives in the time when the world is grappling with Covid-19 and its new deadly variants after every six months. In order to save patients life developing automated ventilation system is the need of the hour. We collected data from several simulations of test lung under different conditions. After preprocessing this dataset using NLP, cross-validation of train and test set. A range of different Machine Learning and Deep Neural Network Models are tried as they can better generalize across lungs with varying characteristics, we scored these models against several evaluation metrics such as MAE, MSE, RMSE. Lastly, we selected best model to predict the target pressure in the respiratory circuit. Through exhaustive clinical tests and accurate medical advice, it is practically possible to bring these results into practical application in future.

**Keywords :** Mechanical Ventilator System, Sedated Artificial Lung, Time-Series Prediction, Machine Learning, Deep Learning, Air Pressure, Covid-19 Variants.

## I. INTRODUCTION

A patient enters a hospital who has trouble in breathing - a patient of COVID 19. The world saw a substantial increase in Covid-19 cases which in turn calls attention to quickly- deployable and cost-effective breathing machines to treat such respiratory ailments. Consequently, it caused a sudden rise of terminally ill patients, who require ventilation support. As mechanical ventilation is a clinically intensive process, one of the constraints that was faced during the early stage of COVID 19. Advancing any new methods for the control of mechanical ventilators is exorbitantly costly. Top notch simulators could diminish this obstruction. Each model of the current simulators simulates a sole lung setting. Simulators being used are prepared like an ensemble. For understanding the differences present in patients' lungs, an approach with suitable parameters should be explored, as the lungs and their characteristics model a steady form. Different settings of mechanical ventilator are chosen relying upon the patient's lung state, and the determination of those boundaries relies upon the noticed patient's reaction and knowledge of the clinicians that are in question.

Essentially, this is not a usual time-series problem. Here we use values of different collections to predict the values of other series.

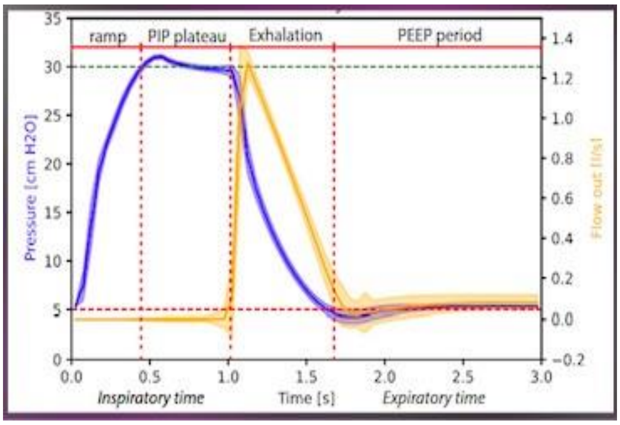


Fig. 1. A typical breath cycle

Great prediction models are constantly beneficial in additional developing setting exactness, decreasing treatment blunders, and fast weaning patients off of the ventilator support to help physicians with this dynamic interaction. It is important to note that positive mechanical breathing gives patients outside assistance till their health improves and they can reconcile with their devices. Volume and pressure control are the most frequent methods of mechanical ventilation. This is not the case with isometric tidal volume. Because of reduced compliance and aggressive exhalation in volume- controlled ventilation, the system may amplify the risk related to lung injury by adjusting pressure of the inspiratory flow and waveform features. Current mechanical ventilators enable doctors to modify a broad variety of parameters, including the mode and intensity of activity, to fit the patient's needs. It is important to know how many obligatory breaths a patient must take and how many extra breaths he or she may take if he or she chooses to do so. The amount of oxygen that is delivered into the body may be regulated from room air (21 percent oxygen) to 100%. To set the PCV air pressure that will be given to the patient, the SetP parameter may be utilized. All airway pressures, namely PEEP and SetP, are added together to calculate the peak inspiratory pressure (PIP). To avoid alveolar collapse between breaths, the ventilator may supply a continuous positive end-expiratory pressure (PEEP). It'll assist with conquering the expense barrier and growing new techniques for controlling mechanical ventilators.

### Objective

The aim of this paper is to forecast the pressure within a mechanical lung at any given time step based on how much the inspiratory solenoid valve (u in; a number between 0 and 100) is opened. The purpose is to imitate a ventilator which is connected to a sedated patient's lung while accounting for lung properties such as compliance and resistance.

## II. RELATED WORK

Over the past few years many traditional mechanical venti- lators prediction systems were introduced but they missed out on the expensive new developed methods and correct pressure as they were manually adjusted by a clinician. Previously a machine learning model based on ANN and optimization was trained with input/output data; it was used to predict mechanical ventilation parameters using the inverse mapping approach. [2] The unique GPSO approach was employed as an optimizer in inverse mapping computations. Extensive simulations were done to evaluate the GPSO's behavior in the feedback loop and to enhance the model's performance [3].
Mechanical ventilator settings were estimated using a ma- chine learning model based on ANN and optimization. After the ANN was trained with

input/output data, it was used to predict mechanical ventilation parameters using the inverse mapping approach. [2] The unique GPSO approach was employed as an optimizer in inverse mapping computations. Extensive simulations were done to evaluate the GPSO's behaviour in the feedback loop and to enhance the model's performance [4].

An AI model dependent on ANN and advancement was worked to assess mechanical ventilator boundaries. The pre- pared organizations were used to appraise mechanical ventila- tion boundaries utilizing the backwards planning procedure after the ANN was prepared with input/yield information.

[2] In reverse planning calculations, a one of a kind GPSO technique was utilized as an enhancer. To survey the conduct of the GPSO utilized in the input circle and to work on the model's exhibition, broad recreations were run [4]. Prediction for mechanical ventilation (MV) in hospitalised patients, including those with COVID-19, was done using generally accessible data from electronic health records, including the VentNet algorithm versus ROX and a logistic regression model that incorporated clinical factors. The algorithm's performance was evaluated based on its AUC, sensitivity, specificity, and positive predictive value (PPV).

Utilizing regularly accessible information from electronic wellbeing records, a straightforward DL calculation was utilized to anticipate the future requirement for MV in hospital- ized patients, incorporating those with COVID-19, utilizing the VentNet calculation against the ROX and a strategic relapse model dependent on generally utilized clinical factors. The region under the beneficiary working trademark bend (AUC), affectability, particularity, and positive prescient worth were utilized to survey the calculation's exhibition [3].

Kilkarni et al [5] By employing a well-known DenseNet121 deep learning architecture, an advanced model was constructed to predict the requirement for breathing using X-ray images three days in advance of the actual intubation incidence.

Ming-YenLin et al.[10] used three Machine Learning mod- els XGBoost, logistic regression(LR), and random forest (RF) to create an explainable weaning prediction model for patients requiring prolonged mechanical ventilation (PMV). The study established that the accuracy of the XGBoost and RF in prediction of successful weaning was high.

Researchers such as Yan Jia et al.[11] introduced Convolu- tion Neural Networks (CNN) for the prediction model in the coming hour for a given patient condition by using historical data from ICU which is extracted from MIMIC-III. The accuracy achieved was 86% by performing feature importance analysis for the CNN and interpreted the features by using the DeepLIFT method. Researchers like Schalekamp et al.[20] used multivariable logistic regression to build a risk model that took into account clinical, computed tomography (CT) scan, and laboratory data to predict severe illness (including invasive ventilation).

DBNet[21], a unique deep learning system that employs a relational database as input with multiple tables. There is no information loss or transformation due to the model's use of many tables from an EHR database. One layer of information that combines cross-sectional and longitudinal data utilising an integrated CNN-RNN encoder-decoder architecture that can handle varying durations of observations and several data modalities at the same time.

## III. PROPOSED METHODOLOGY

Working to solve time-series forecasting problem by applying common machine learning methods and deep learning algorithms is not uncommon. As can be seen from the experimental results, generally deep learning approaches work better than traditional machine learning methods. Our project methodology revolves around some competent forecasting approaches such as LSTM and Bi-LSTM. All these sequential deep learning models are nothing but subtypes of Recurrent Neural Networks (RNN). In case of sequential data like time-series data used here, data at time (t) depends on data at time (t-1). RNN being a feed forward neural network can easily remember what happened previously in sequential data which helps them in deriving correlations and patterns in the domain of predictive analytics.

4.1 Machine Learning

Linear Regression (LR): It is a renown supervised learning algorithm to perform regression tasks. It can also be defined as a statistical model which shows the relationship between two variables and forecasting with the linear equation.

Random Forest (RF): It is a versatile algorithm as it can perform regression and classification tasks both. It is an ensemble of decision trees on varying samples. It has an important feature of handling continuous dataset variables in case of regression.

K-Nearest Neighbour (kNN): It can also perform regression and classification tasks both. It calculates distance between two points in the dataset using similarity between attributes.

Light Gradient Boosting Machine (LGBM): It is a variant of the gradient boosting frameworks. It is supposed to be distributed, fast and also high-performance. It is based on the decision tree algorithm.

4.2 Deep Neural Networks

Multi-Layer Perceptron (MLP): This is a completely connected, feed forward neural network. This is a perceptron that attaches itself with several layers of additional perceptrons to solve numerous complex problems including time series data forecasting, recognition of gestures and prediction.

LSTM: For a variety of learning issues involving sequential input, recurrent neural networks (RNN) with long short-term memory (LSTM) have emerged as an efficient and robust technique. Because they are broad and effective, they are excellent for capturing long-term temporal dependencies.

Bi-directional LSTM: Bi-LSTM is known to train a network using both past and future data sequences as inputs. Two linked layers are used to process the input data. Bi-LSTM uses a finite sequence to forecast or tag the sequence of each element depending on the context of components in the past and future.

4.3 Optimization of hyperparameter

Adam Optimizer, a highly effective optimization algorithm, employed as an alternative to traditional gradient descent procedures for updation of weights in a neural network on the basis of training data. Parameters such as learning rate controls shifting of the rate of decays.

## IV. EXPERIMENTAL SETUP

5.1 System Overview

To obtain medical data and test experiments a IOT-enabled system is developed by researchers and tech-professionals in the laboratory conditions. A lot of data was generated from a modified open-source mechanical ventilator (PVP-The People's Ventilator Project) [1] connected to an artificial test lung (Quick Test Lung) in a respiratory circuit. Artificial test lungs are more effective than the bladder-style test lung as they provide linear and predictable respiratory simulation. Pressure sensor records the amount of air absorbed and released by the test lung. This model helps in generation of dataset. A portion of this generated data for the use of medical and patient's treatment, including mechanical breathing.

The System software for the project is written in high-level Python (3.7) and even the hardware components are not medical-related devices but readily available components for instance specialized respiratory circuits and HEPA filters. In a real experimental set-up, an artificial bellow-style Lung along with a pressure analyzer is used for accurately testing the performance of mechanical ventilation in the presence of an open-source, low-cost pressure control ventilation system developed in Princeton Lab intended for research purpose only in response to shortage of trained-professionals during Covid- 19 pandemic, to provide ventilation to patients mechanically who face trouble in regular breathing. In order to automate the ventilator, a control has been applied on air pressure in the ventilator in the Fig.2 mechanically so that it can respond accurately in different lung settings during the inspiratory phase in the human respiration.

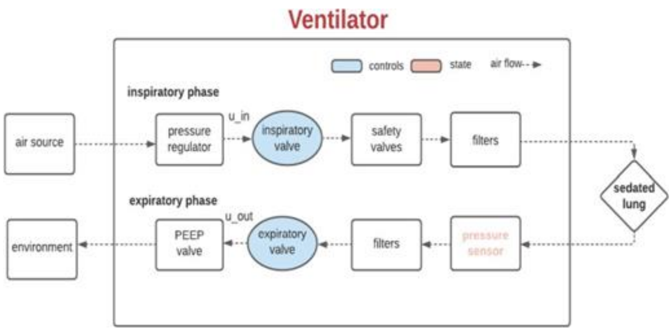


Fig. 2. Block Diagram of Mechanical Ventilator performing Simulation

5.2 Dataset

We performed our analysis on the research dataset launched by Google Brain in September 2021 on the kaggle platform. Ventilator Prediction dataset provides numerous time series of breaths and time series of control inputs of the mechanical ventilator data for training our time series models. It is a large- scale dataset with ventilator characteristics of multiple training samples where each sample is a time step in breath, giving two control signals, lung attributes and target airway pressure. Specifically, it is a time series data collected over a period as pressure data. Each time series represents approximately three seconds of a breath. The training set consists of 8 attributes of Ventilator, shown in the table I. In this ventilator-lung system, lung attributes are R and C and two control inputs each during inspiratory and expiratory phase in the given respiratory circuit. Here, our 'Target' is the dependent variable, which is nothing but a continuous variable, airway 'Pressure' during the inspiratory phase of the respiratory circuit. We are provided with csv file consisting of 7 attributes (except the 'Target') as a test data.

5.3 Exploratory Data Analysis

This step helped us to derive extra meaningful information from this huge ventilator dataset for our analysis besides what is already given. A set of python libraries is utilized to interpret the dataset in a better manner using statistical, graphics and other data visualization methods. Fig. 3 shows the visualization of a sample breath for a particular breath id (Breath id: 1, R: 20, C:50) we can observe that first the target pressure is uprising and then, after it when the u out becomes equal to 1, pressure drops abruptly.

A fairly balanced distribution of combinations of R and C data points is helpful in predicting each example in unknown

TABLE I. DESCRIPTION OF THE DATASET

| **Attributes** | **Accepted Value** | **Nature of Variable** | **Description** |
|---|---|---|---|
| id | 1 onwards | Continuous | Globally-unique time step identifier across an entire file |
| breath id | 0 to 2245 | Continuous | Globally-unique time step for breaths |
| R | [5,20,50] | Categorical | Represents the percentage of inspiratory solenoid valve open to let air into the lung(i.e., 0 is completely closed and no air is let in and 100 is completely open). |
| C | [10,20,50] | Categorical | Represents when the exploratory valve is open(1) or closed(0) to let the air out of the respiratory circuit. |
| time step | Actual time stamps | Continuous | It represents amount of time the breath took. |
| u in | 0 to 100 | Continuous | The control input for the inspiratory solenoid valve. |
| u out | 0 or 1 | Categorical | The control input for the exploratory solenoid valve. |
| pressure | measured in cmH20 | Continuous | The airway pressure measured in the respiratory circuit. |

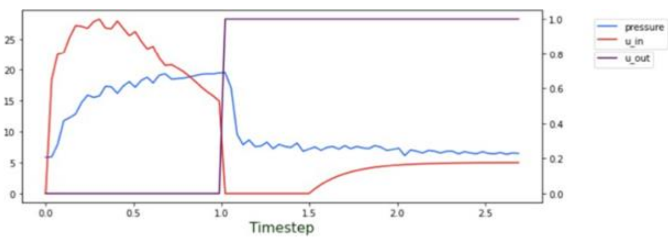


Fig. 3. Sample breath for a particular breath id in the train set

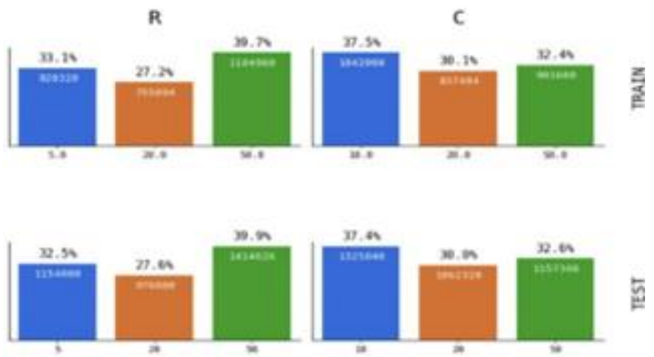


Fig. 4. Distribution of R and C values in the train and test set

Test data with equal probability. Fig. 4 shown above represents categorical variables such as R and C have identical distribution in train and test set. From the correlation matrix of features in Fig. 5, it is quite evident that, a moderately negative correlation exists between the target class 'pressure' and control input of exploratory solenoid valve 'u_out', also 'u out shows high positive correlation with time. Comparatively, 'u in' has a good positive correlation with 'pressure' than with other attributes.

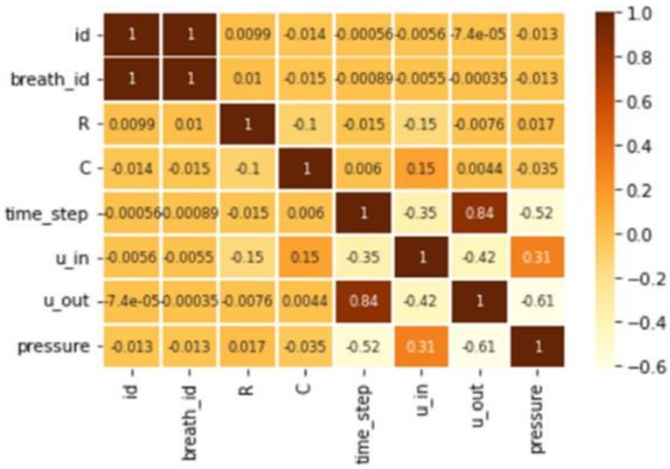


Fig. 5. Pearson correlation of Features for the ventilator dataset

5.4 Preprocessing and Feature Engineering

We checked for any null or duplicate values in both test and train set and removed these examples when found. Before feeding this complex real-time data to the neural network, it is important to remove certain unexpected observations by normalization on rare instances of both test and train set using the transform method of robust scaler class in scikit-learn library. Compared to other normalizers, it removes median and scales of data using the range between quantiles.

This was followed by feature engineering in which we selected few important features and and transformed them to generate additional attributes which could help in training the model. Here, for instance by grouping u in of a particular breath id. In that particular breath we can find the maximum amount of air inhaled ('breath id u in max'), mean amount of air inhaled for a breath ('breath id u in mean') and also find out how much u in in each sample for a particular breath deviate from max u in value ('breath id u in diffmax') and from mean u in value ('breath id u in diffmean').

5.5 Experimental Configuration of ML Models

After feature engineering, we split the training and test set in the 7:3 ratio. We scaled the dataset by performing 5-fold cross- validation on this train set and test set. We used a collection of machine learning regressors here, such as Linear Regression, kNN, XGBoost, Light Gradient Boosted Machine and Random Forest.

TABLE II. SCORING SUPERVISED MACHINE LEARNING MODELS

| Supervised ML Algorithms | R-squared | MAPE |
|---|---|---|
| Linear Regression | 0.380519 | 37.565245 |
| LightGBM Regression | 0.443025 | 34.115820 |
| K-Nearest Neighbors | 0.702278 | 22.119794 |
| XGBoost | 0.434124 | 34.245190 |
| Random Forest | 0.295020 | 36.808463 |

5.6 Experimental Configuration of Neural Networks

We constructed a bunch of DNN models based on MLP, LSTM with two hidden layers and Bi-LSTM with eight hidden layers. After this, these neural network models were trained for updation of weights to learn the behavior of data, here, we tried to minimize the time taken to perform update using adam optimization algorithm where the parametric value for the learning rate equals to (1 x 10–3 for Bidirectional LSTM) and (0.5 x 10–3 for LSTM) models.

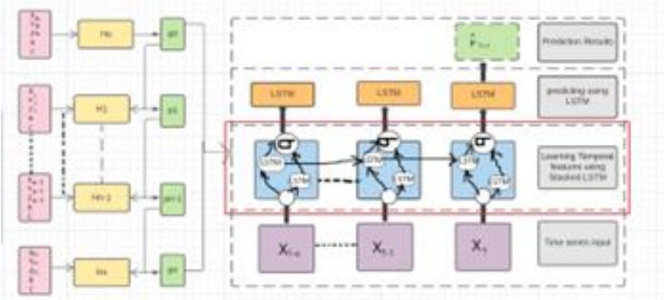

Fig. 6. Network Architecture for our implemented Bi-LSTM Model. For the architecture of our implemented LSTM Model just remove the Stacked LSTM layer.

## V. Evaluation and Comparison of Results

During the evaluation, we calculated training error loss to compare performance of the models based on different algorithms. Score of mean absolute error i.e MAE, (also called as L1 loss) , mean square error (MSE) and root mean square error (RMSE) between the predicted and actual pressures during the inspiratory phase of each breath was recorded for each trained model. We can clearly see the expiratory phase is not scored here. Probably, the scores are only calculated during the inspiratory phase because u in profiles in the expiratory phase didn't change much across different simulations and would not be much valuable to study. Score of evaluation metrics used are given by:

$$MAE(X, Y) = |X - Y| \quad (1)$$

$$MSE(X, Y) = (X - Y)^2 \quad (2)$$

$$RMSE(X, Y) = (X - Y)^2 \quad (3)$$

where X is the vector of predicted pressure and Y is the vector of actual pressures across all breaths in the test set. At the end of each iteration, loss is recorded while training our models with training set. Similarly, loss for the validation set is calculated after recording the error after each epoch. We observed that loss during each epoch dropped, this decreasing loss with respect to epochs is the learning curve for LSTM (as shown in Fig. 7) and Bi-LSTM (as shown in Fig. 8) models implemented here.

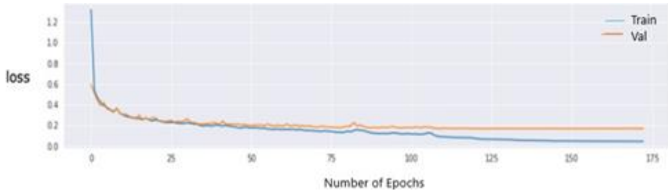


Fig. 7. Variation of the training loss and validation loss over time for LSTM Model

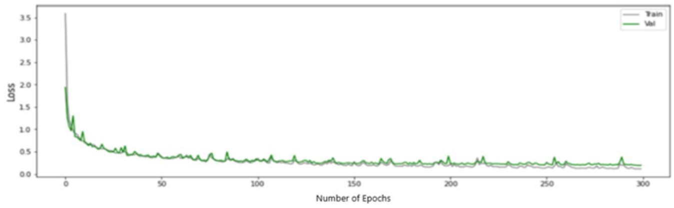

Fig. 8. Variation of the training loss and validation loss over time for Bi-LSTM Model

We have mentioned Overall L1 Loss,MSE and RMSE of all the algorithms we used in the Table III. From the column of mean absolute error loss (0.161112) in Table III, we can observe that Bi-LTSM model gives minimum loss (4.029514) among all, whereas the performance of supervised machine learning algorithm i.e. Linear Regression is worst among them all. From the mean square error loss in Table III, we can observe that Bi-LTSM model gives minimum loss (1.05818) among all, whereas the Linear Regression Model gives maximum mean square error (20.26328) in the computation of predictions. Based on the results, root mean square error for Linear Regression is 4.50148 whereas LSTM model with 1.65735 and Bi-LSTM model with 1.02868 loss impressively, outperforms rest of the techniques used.

TABLE III. COMPARISON OF RESULTS

| Algorithm Used | Overall L1 Loss | MSE | RMSE |
|---|---|---|---|
| Linear Regression | 4.029514 | 20.26328 | 4.50148 |
| K-Nearest Neighbors | 2.211979 | 19.576831 | 4.42457 |
| Multi-Layer Perceptron | 2.557977 | 12.86334 | 3.58655 |
| LightGBM | 2.125771 | 10.68989 | 3.26954 |
| Random Forest | 1.308497 | 6.58006 | 2.56516 |
| LSTM | 0.418213 | 2.74681 | 1.65735 |
| Bi-LSTM | 0.161112 | 1.05818 | 1.02868 |

## VI. LIMITATIONS OF THIS WORK

On the basis of our results of our proposed work, post the training and evaluation of our models on the dataset. We can draw some observations on the possible drawbacks of our study, a few of which are listed below:

1) Given the dataset we have, the solution might not be able to generalize to real word scenarios.

2) Simulated data is not considered real environment data even though the neural network model was learning the pattern existed in data. But since it was driven by a PID Controller we ended up learning the behavior of PID Controller while training our model.

3) Though we could fit in the data, but the way data was generated could have improved a bit.

4) Values of pulmonary parameters such as R and C, didn't have any considerable effect on our results. From the experimental observations we observed that even after changing R and C values and training the model deep enough didn't have much impact. We assume this could be because the pressure is only dependent on immediate previous u in values.

## VII. CONCLUSION

In this paper we have used ventilator pressure prediction dataset published by Google Brain on the Kaggle platform using the data generated by the open-source ventilation system developed by Princeton Lab researchers for our analysis. We performed exploratory data analysis on the large dataset followed by data pre-processing. We considered this as a regression problem and split the dataset into train and test data. After this various machine learning algorithms and a bunch of deep learning algorithms were used for training our model separately. Out of which the deep learning approaches such as LSTM and Bi-LSTM outperformed outperformed the machine learning-based and other deep learning-based regression models in terms of prediction. Further, the results revealed that BiLSTM-based modelling, which incorporates additional data training, provides better forecasts than normal LSTM-based models. Thus, providing the model with additional training data can be useful for future predictions.The proposed study utilizes data analysis, deep learning architectures and machine algorithms to optimize the control of ventilator, showed what can be accomplished by learning the whole pressure-control system from the ground up. Practically, in the wake of the unforeseen outbreak of Covid- 19 pandemic, the deep neural network models developed in this work may be useful in forecasting mechanical ventilation settings for the survival of patients inflicted with respiratory diseases. Using a neural network, it is possible to replicate the lung-ventilator system's nonlinear dynamical system more precisely than with earlier physics-based models. But as the dataset was taken from a simulator-based lung setting which is not clinically validated results in uncertainty for the real-world scenarios, to test its efficacy on living organisms correct medical recommendations are required. To initiate its regular operation few changes in design of the device are essential to make it portable and convenient for everyday use in homes and hospitals by any individual.

## VIII. FUTURE SCOPE

In our future work, we would like to use a transformer-based framework for multivariate time series analysis. Instead of using mean as done in our technique, in future, median can be used as a statistical measure to ensemble fold predictions of the model in consideration. To increase the accuracy of predictions, rounding of the actual pressure in the training data can also be done to closely match with the discrete target predictions. To reduce training error in future notebooks, we have to avoid over-fitting the training set with several features. We can fix this by adding regularization and also through early stopping to avoid overt-raining neural networks. Since, we also have multiple attributes in the dataset some of which have categorical values too, we can consider this problem as a classification problem instead of regression as done here to predict the pressure for each training example. Further, we could also try experimenting with other neural networks like multilayer perceptrons, convolution neural network ensemble of LSTM or BILSTM-CNN. Additionally, we can aim to use a powerful GPU to speed up the training process.

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