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ORIGINAL RESEARCH ARTICLE

Lung pressure predictive model using LSTM: A deep learning techniques

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ABSTRACT

The human body relies on controlled breathing to ensure oxygen reaches all cells while filtering out contaminants to protect the lungs. However, infections like the Delta virus and SARS-CoV2 (COVID-19) have led to Acute Respiratory Distress Syndrome (ARDS), requiring urgent medical care, including mechanical ventilation. The overwhelming number of patients has strained healthcare organizations and workers, necessitating advancements in automated healthcare technology. To address this challenge, we propose a novel solution to predict pressure in mechanical ventilation (MV) for various lung illnesses. The goal is to accurately predict the pressure within the respiratory circuit, which poses a challenging sequence prediction issue. To tackle this, we employ a cutting-edge deep learning approach known as Long Short-Term Memory (LSTM), which exhibits remarkable performance in selectively recalling patterns over time. While traditional recurrent neural networks (RNNs) can handle short-term patterns well, the introduced LSTM technique excels in managing complex sequence prediction problems. Comparing the proposed method with four existing algorithms, the researchers demonstrate that their approach achieves significantly higher accuracy. The impressively low error rate of 1.85×10^{-7} showcases a substantial improvement over existing system. This groundbreaking advancement has the potential to alleviate the pressure on the current healthcare infrastructure and significantly improve care for patients in need of mechanical ventilation due to respiratory issues.

Keywords: LSTM; deep learning; lung pressure prediction; RNN; COVID-19

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1. Introduction

The lungs are the main organs that are active in the process of breathing in and out. A human being's lungs may be found on both the left and right sides of their chest. The size of the left lung is much less than that of the right lung, which frees up more room for the heart. With each breath, the chest goes through a rhythmic expansion and contraction. This is because the lungs expand during inhalation, but contract during exhalation. The reason for this is because the lungs expand during inhalation but contract during exhalation. Bringing oxygen into the circulation is the job of the lungs, which are the organs that make up the respiratory system. Blood that is low in oxygen and rich in carbon dioxide is pumped from the heart to the lungs by the heart. The lungs then take this blood in via the air that they breathe. During the process that is referred to as "cleaning", the blood that is found inside the lungs goes through a series of events in which it takes in oxygen and releases carbon dioxide. When a person breathes out, they give off carbon dioxide into the air, and when they breathe in, oxygen is absorbed into their lungs[1].

Lung problems are one of the leading killers in developed nations. Smoking, toxic environments, and chronic inflammation are just a few of the factors that have negative impacts that often result in lasting injury. Failure of the lungs may cease breathing, which can cause death. Numerous diseases and ailments, such as pneumonia, heart failure, COVID-19, and many more, may result in lung failure. A person who is unable to breathe on their own or who has respiratory problems needs some kind of external support in order to help them breathe. The patient uses a mechanical ventilator to get this assistance, but if they're in a stable condition, they'll be weaned off of it and won't require it anymore[2]. The oxygen content in the patient is automatically adjusted by MV using a Proportional Integral Derivative (PID) control algorithm in accordance with the patient's needs. The patient's breathing frequency, oxygen level, and other physiological data points are used by these controllers to assist the patient stabilize and provide the right quantity of oxygen. The system's inputs include the oxygen and carbon dioxide concentrations as well as air resistance. These ventilators are designed to respond to changes in the patient's breathing frequency by assisting in the adjustment of the patient's breathing frequency in a manner that is clinically appropriate. Medical professionals with the necessary training control and operate mechanical ventilators in a clinical setting[2]. **Figure 1** shows working of the mechanical ventilator[3].

However, there are several restrictions associated with PID controllers. When it comes to an integrated process with a large degree of time delay, performance is poor. It is difficult to accurately depict subtle changes or deviations. There is need of Artificial Intelligence (AI) based or automated ventilator which can be used by the medical practitioner easily which can control pressure automatically and can use limited amount of oxygen which is required to heal up the patient. So this paper proposes a deep learning based lunges pressure prediction system which can be used by the machine to control the presses and also save the oxygen.

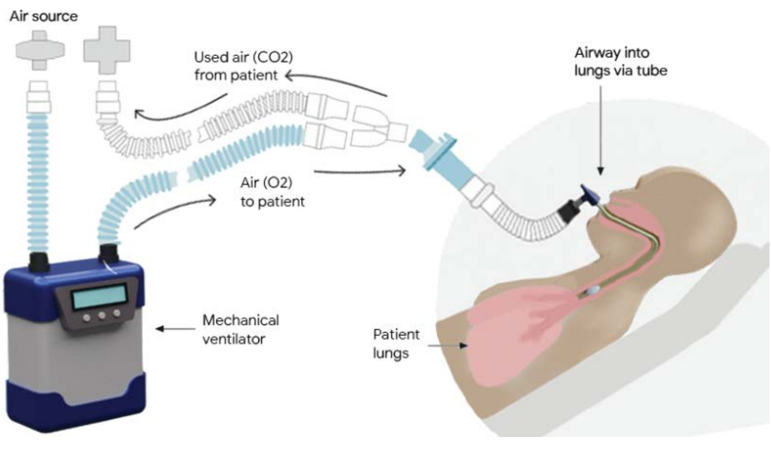

Figure 1. Mechanical ventilator.

The suggested solution aims to do away with PID controller's restrictions. Deep learning as proposed can function more efficiently. The healthcare system can afford the recommended strategy. One patient will need fewer workers to ventilate, which might be beneficial, especially in pandemic situations. The acute respiratory syndrome has been responsible for the deaths of 2.2% of all COVID-19 infected people worldwide since November 2019, according to data from the Virus Centre at Johns Hopkins Medicine. Ground Glass Opacity (GGO) analysis has shown that COVID-19 mutations, in particular Delta 1, are to blame for pneumonia in both lungs. Many people who have been infected with Delta or one of its variants need sophisticated medical treatment, such as invasive mechanical ventilation, due to their ARDS. The main study focus is on the effects of COVID-19 variants on the immune system, ground-glass opacity, and the many neoplastic changes that take place in the lungs as a consequence of attacks by SARS-CoV2 and other variants.

Over 170 nations all over the globe have been impacted by the pandemic that is caused by COVID-19. Nearly all of the countries that have been hit have seen an alarming rise in the number of people who have died from the disease as well as those who have been infected. Many of them loss there life due lack of ventilator or Oxygen supply[4]. Details on mechanical ventilators and how they are used in the COVID-19 pandemic are provided in this section. The necessity for an AI-based autonomous ventilator is also mentioned, which may aid the healthcare system by enhancing ventilator efficiency and reducing oxygen use.

Section 2 reviews some of the method used for lung pressure prediction and its application. Section 3 presents the suggested deep learning algorithm. Section 4 carries out experiments and analyses the results. In Section 5, the study is finished.

2. Related work

In this section, we will present a detail overview of the most recent research that have been done for the purpose of predicting the development of lung pressure using AI methods and models.

Hess DR cover basic and advanced respiratory mechanics during mechanical ventilation[5]. He says patients who are being mechanically ventilated might have a number of different respiratory mechanics evaluated. This may be helpful as an investigation into the underlying pathophysiology of the condition. In order to prevent lung damage, an assessment of the patient’s respiratory mechanics may also be utilized to adjust the ventilator. Author suggested that there is need of automated ventilator which can control advance and basic respiratory. Marchuk et al. demonstrates the feasibility of using the Hidden Markov Model (HMM) algorithm to predict ventilator pressure in sedated patients[6]. The study concludes that there is a high probability of this event occurring at the chosen threshold value. Unlike previous research that was based on short observations of patients with specific conditions, the authors of this study analyzed the entire mechanical ventilation period of a diverse group of critically ill ICU patients suffering from a range of illnesses.

According to the Gunasinghe et al., the early diagnosis and prediction of lung illnesses have become crucial in research since they may aid in the usual diagnostic treatment of patients[7]. A machine learning-based decision support system aids doctors in making decisions regarding their diagnosis. In addition to lung cancer, asthma, chronic obstructive pulmonary disease (COPD), TB, and pneumothorax, the author’s research included patients’ breathing problems. The use of a ventilator when it was urgently required was brought on by the whole sickness. The choice of parameters for patients is based on their medical monitoring, previous medical history, and the clinical expertise of the treating physicians. Oruganti Venkata et al. examine the impact of different ventilator settings on patient lung health[8]. They use a Graded Particle Swarm Optimizer to analyze the medical data of patients. However, a disadvantage of the study is that patient information was manually entered and ventilator parameter values were only collected at random times, not continuously.

Kulkarni et al. suggest using chest X-ray images of hospitalized COVID-19 patients to determine the need for mechanical ventilation[9]. They collected 663 X-ray images from 528 patients and applied the DenseNet121 deep learning architecture. The images were independently and blindly evaluated by two pulmonary and critical care experts for validation. Yu et al. propose method using machine learning to predict mechanical ventilation and mortality in COVID-19 patients[10]. The authors used information from 1980 on all COVID-19 patients to make their predictions. They trained the XGBoost algorithm on demographic information, medical histories, ER vital signs, laboratory values, therapies, and smoking and drinking histories of 1036 patients and validated it on 674 more patients. To predict in-hospital mortality, they studied 3491 ER patients using CatBoost for training and validation.

Le et al. present a method for early detection of Acute Respiratory Distress Syndrome (ARDS) using supervised machine learning[11]. The study was based on 9919 patient interactions in the Medical Information Mart for Intensive Care III (MIMIC-III) database. The XGBoost gradient boosted tree models for ARDS prediction were created using routine clinical data and numerical representations of radiology reports as inputs. The models were trained and validated using 10-fold cross-validation. Sayed et al. aim to predict the duration of mechanical ventilation in Acute Respiratory Distress Syndrome using supervised machine learning[12]. The authors obtained data from the first three ICU days after ARDS diagnosis from the MIMIC-III database. During those three days, they monitored the progression of the illness to calculate the lung severity using the Berlin criteria. Three trustworthy supervised machine learning methods were developed for MV time prediction using Python 3.7: Light Gradient Boosting Machine (LightGBM), Random Forest (RF), and XGBoost. The eICU database was used for external validation.

Patil et al. propose Medical Cyber Physical system for upcoming society, i.e., society 5.0. e-Healthcare will be the subject of most study in society 5.0[13]. Mechanical ventilator powered by AI will improve the e-Healthcare system. Which may control the pressure of the ventilator and keep an eye on the patient's breathing.

The studies reviewed aim to predict the pressure of mechanical ventilators for patients with lung disorders[5–13]. Some studies use machine learning algorithms like HMMs, GPSO, DenseNet121, XGBoost, LightGBM, Random Forest, and CatBoost to predict pressure. Other studies propose a decision support system and a Medical Cyber Physical system to improve the e-Healthcare system. The studies have used diverse patient populations and datasets, including COVID-19 patients and data from MIMIC-III and eICU databases. All of the studies mentioned in Section 2 make an effort to estimate the pressure of the mechanical ventilator, and most of them have utilized the COVID-19 dataset to do so. The outcomes of every strategy are advantageous for the modern civilization. But lung-related illnesses are also on the rise as the population grows every day. Thus, we need a more effective and precise approach to predict the pressure of the mechanical ventilator for the forthcoming society 5.0. In the study, an effort is made to find a better approach to predict pressure.

3. Proposed algorithm

The proposed methodology for predicting lung pressure is illustrated in **Figure 2**. The initial step involves data collection, dataset generation, and extraction of relevant information from the dataset. Subsequently, the gathered data undergoes preprocessing, including feature extraction and scaling. The dataset is then divided into a training set and a sample set. A deep learning-based LSTM model is trained using the training set. The model is trained to learn patterns and relationships within the data. Following training, the model is evaluated using the test data to predict the desired outcome. The performance of the model is assessed based on various metrics, such as accuracy.

If the model's accuracy falls below the desired threshold or if the model exhibits weaknesses, the process from feature extraction is repeated. This iterative approach continues until the model achieves satisfactory accuracy and stability, ensuring consistent results across multiple iterations. Once the model meets the desired criteria, it can be implemented in applications for smart healthcare systems. The trained model can be integrated into these systems to provide accurate predictions of lung pressure, enabling better monitoring and management of respiratory health. The proposed methodology involves data collection, preprocessing, LSTM model training, iterative refinement, and implementation in smart healthcare applications to facilitate reliable predictions of lung pressure.

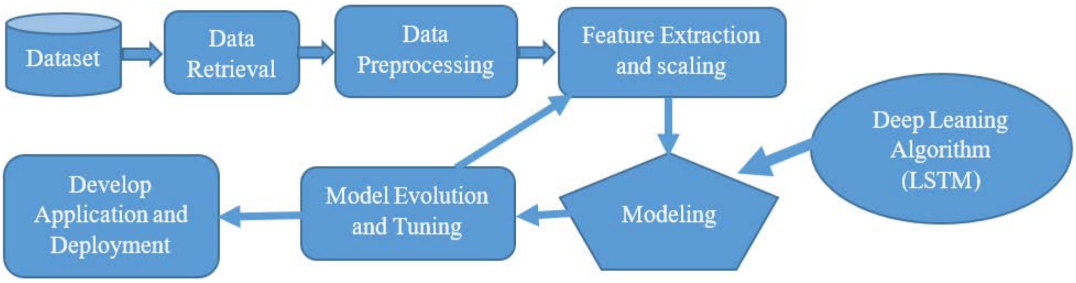

Figure 2. Proposed system engineering framework.

In proposed system **Figure 2**, we are going to use LSTM which is deep learning algorithm. To study LSTM we need to study neural network and recurrent neural network.

3.1. Recurrent neural networks

To comprehend RNN, it is essential to first comprehend what a neural network is. A neural network is a collection of algorithms that, by imitating the functions of the human brain, find patterns in input data. Artificial Intelligence and machine learning both employ neural networks. Other data kinds, such audio, video, and still images, must first be converted into a mathematical form since they can only detect patterns in numerical or vector data[14]. A "recurrent neural network (RNN)" is a feed-forward neural network derivative. The results of one computation are used as inputs for subsequent calculations in this kind of neural network. The outcome of the most recent calculation will be copied by RNNs, and it will be concealed in a state. The value that was buried in the previous calculation is taken into account in the subsequent computation together with the input that was given for that step. RNN has been determined to be one of the most effective models for handling data of this sort. The data that are included in the dataset that we have or that we utilize are in the form of a sequence. Using their internal state, RNNs can process input sequences of different lengths (memory)[15].

Figure 3 shows the working of RNNs in which H is the hidden layer, X and Y are input and output layers respectively, W_x is weight associate with current input, W_y is weight associate with output and W_h is weight associated with hidden state. The RNN algorithm is based on the idea that the output of each layer is stored and then fed back into the system's input in order to anticipate the output of the corresponding layer. A single layer of recurrent neural networks, denoted as H, is created by compressing the nodes from several layers of the neural network. The current input is a mixture of the input at $x(t)$ and $x(t-1)$ at any given time t. To enhance the output, the output at any given time is fetched back to the network.

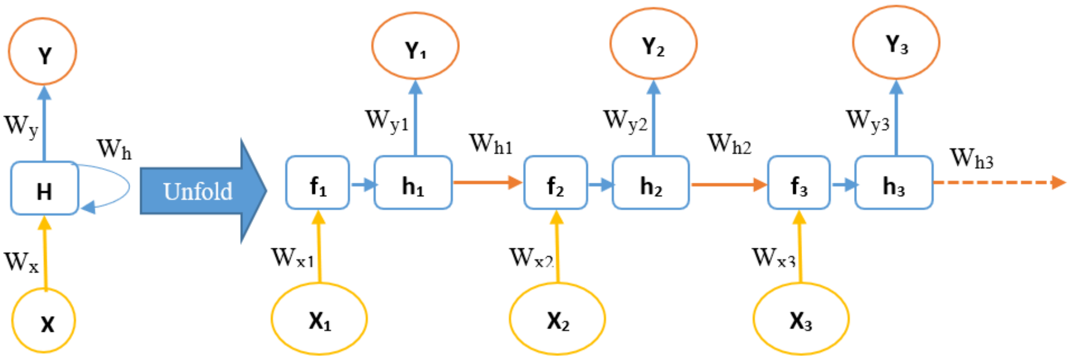

Figure 3. Working of RNNs.

Current state equation is given by Equation (1).

$$h_t = f(h_{t-1}, X_t) \tag{1}$$

Applying tan activation function to the current state is given by Equation (2).

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}X_t) \quad (2)$$

where W_{hh} is the weight at the previous hidden state, h_{t-1} is previous hidden state calculated by Equation (1), W_{xh} is current hidden state input weight. X_t is current input. Y_t is the output of current state and given by Equation (3).

$$Y_t = W_{yh}h_t \quad (3)$$

where W_{yh} the weight at the current output state. The benefit of using RNN in this situation is that it can model a series of data to create a model that yields conclusions that rely on the data that came before it. In addition, managing a lengthy data sequence is challenging when using an activation function. In this situation, the LSTM framework is used.

3.2. Long Short-Term Memory network

Modern recurrent neural networks include LSTM networks, which have a memory and can process a large sequence of input more quickly. By retaining knowledge for a long time, it has capability to learn long-term dependencies. Here, the issue of RNNs not having enough memory to retain previously recorded data in hidden states for a longer length of time is resolved. The LSTM contains three gates that aid it in making decisions and functions quite similarly to a logic circuit[16,17]. **Figure 4** represents working of 1 recurrence of LSTM where C is the current cell sate.

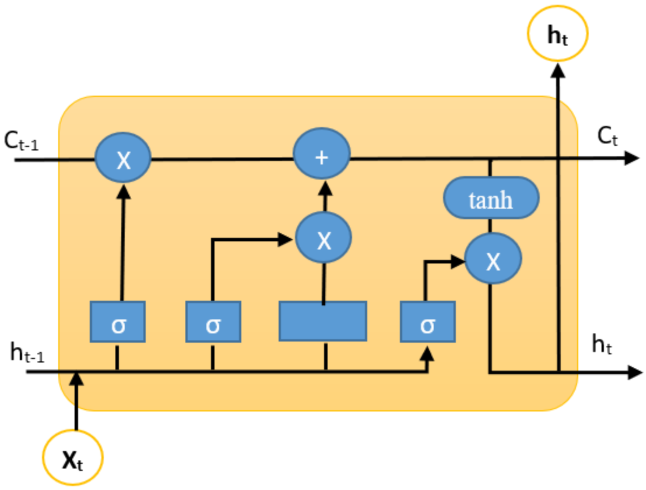

Figure 4. Working of LSTM.

LSTMs operate in a three-step process called the "input-forget-output" gate mechanism:

1) Input gate: the model decides which values should be updated in the cell state.
2) Forget gate: the model decides which parts of the cell state should be discarded or forgotten.
3) Output gate: the model decides what to output based on the updated cell state. This output is then used as input to the next time step in the sequence.

Which data should not be included in the cell at that time step is decided by the sigmoid function. Both the current state (X_t) and the previous state are taken into account while calculating the function (h_{t-1}). The sigmoid function is used to determine the values of these gates, yielding values that fall between 0 and 1. The disappearing and expanding gradient issues that might arise in conventional recurrent neural networks are solved by LSTMs thanks to these gates (RNNs). For the three gates in Equations (4)–(6), the letters I, F, and O stand for input, forget, and output gates, respectively. Each of the letters X, H, W, and b stands for input data, hidden state, weights, and biases.

$$I_t = \sigma(X_tW_{xi} + H_{t-1}W_{hi} + b_i) \quad (4)$$

$$F_t = \sigma(X_tW_{xf} + H_{t-1}W_{hf} + b_f) \quad (5)$$

$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o) \tag{6}$$

The memory cell, sometimes referred to as the candidate memory cell Mc, is an extra crucial component of an LSTM network. With the exception of using the tanh function rather than the sigmoid function, the value of the candidate is determined similarly to how the three gates are determined. This results in values that fall between the range of −1 and 1. In an LSTM network, the forget gate is responsible for determining how much of the information that has been stored in the candidate memory as a result of previous computations is retained, and the input gate is in charge of determining whether or not new information should be added to the candidate memory during the course of the current computation. A mathematical depiction of this process is given by the formula in Equation (7).

$$Mc_t = F_t \odot Mc_{t-1} + I_t \odot Mc_t \tag{7}$$

The concealed state cannot be discovered until the LSTM computation is finished. To achieve this, one must compute the candidate memory's tanh, which produces values between −1 and 1. After that, the output, which may be any value between 0 and 1, is multiplied by the result. All of the data from the candidate memory is transmitted to the hidden state if the output is close to 1. On the other hand, no information is sent if the output is near to 0. Equation (8) provides the equation for the hidden state.

$$H_t = O_t \odot \tanh(Mc_t) \tag{8}$$

When performing tasks requiring the collection of both short-term and long-term dependencies in the data, such as natural language processing, audio recognition, and time series prediction, LSTMs are often utilized[18]. They are a popular option in many machine learning and data analysis applications since using LSTMs instead of conventional RNNs may boost accuracy and performance.

In the field of respiratory mechanics, accurate prediction of lung pressure is important for monitoring patient health and managing respiratory diseases. LSTMs are well suited for this task because they are able to handle sequential data, such as time series data of lung pressure measurements, and capture both short-term and long-term dependencies in the data. In a deep learning approach, LSTMs are trained on a large dataset of lung pressure measurements, using the input features, such as flow rate and tidal volume, to predict the corresponding lung pressure.

The trained LSTM model can then be used to make real-time predictions of lung pressure in a clinical setting. This approach has the potential to improve the accuracy and efficiency of lung pressure monitoring, as well as provide important insights into the dynamics of respiratory mechanics.

In the results and findings section, the performance of the deep learning approach for lung pressure prediction using LSTM is evaluated and analyzed.

4. Result and discussion

The proposed algorithm introduces a novel deep learning methodology using Long Short-Term Memory (LSTM) networks for lung pressure prediction in mechanical ventilation (MV). The key novelty lies in LSTM's ability to selectively retain and recall relevant patterns over time, making it particularly suitable for handling complex sequence prediction problems. To predict lung pressure, the proposed model is trained on a dataset of respiratory circuit pressure readings from patients with various lung illnesses. The LSTM network learns from the sequential patterns in the data and can accurately forecast the pressure within the respiratory circuit, enabling early detection of changes and facilitating timely interventions for patients in need of mechanical ventilation due to respiratory issues.

The results of the deep learning approach for lung pressure prediction using LSTM were evaluated on a dataset of lung pressure measurements from patients undergoing mechanical ventilation. A modified opensource ventilator[19] was used to create the dataset, and it was then coupled to an artificial bellows[20] test lung through a respiratory circuit. Dataset consists of 7600 test data and 50,800 train data.

Features used in dataset is described below:

1) Id—Global and Unique time step identity throughout an entire file.

2) breathed—Global and Unique time step for breaths.

3) *R*—lung characteristic that indicates the degree to which the airway is limited (measured in $cmH_2O/L/S$). In terms of physics, this refers to the ratio of the change in pressure to the change in flow (air volume per time). One may intuitively picture inflating a balloon by blowing air into it with a straw. We are able to alter *R* by adjusting the diameter of the straw; a higher *R* results in a more challenging blow.

4) *C*—lung characteristic giving an indication of how compliant the lung is (measured in mL/cmH_2O). In terms of the physical world, this is the ratio of the change in volume to the change in pressure. The identical balloon scenario may be pictured in one's head intuitively as well. We are able to vary *C* by altering the thickness of the balloon's latex, with greater *C* resulting in latex that is simpler to inflate up and has a lower thickness overall.

5) time step—the actual time.

6) u_{in}—an input for controlling the inspiratory solenoid valve. varies from 0 to 100 and back again.

7) u_{out}—an input for controlling the exploratory solenoid valve. Either a zero or a one.

8) pressure—the pressure in the airways as measured by the respiratory circuit, expressed in centimeters of mercury.

Implementation is done by a personal computer with following configurations:

Processor: Intel(R) Core(TM) i5-8250U CPU @ 1.60 GHz 1.80 GHz
RAM: 8 GB
System Type: 64-bit operating system, x64-based processor
Windows 10
Software and tools used: Python 3.10.4, Jupyter Notebook, Visual Studio Code, StreamLit Library
Database: MySQL
Library used: Pandas, NumPy, Pytorch, TensorFlow, Sci-Kit Learn, Matplotlib

The application that was designed for predicting lung pressure using LSTM is a web application that was constructed with the help of the StreamLit library and the programming language Python. Visual Studio Code was used to carry out the execution, and the code is being processed by a localhost server.

The term "array of projected pressures" refers to a collection of forecasts on future pressure values in a lung pressure time series created by a machine learning model, in this example, a LSTM model. Each member of the array, which stores these predictions, corresponds to the projected pressure value for a certain time step. The average of all the forecasts recorded in the array is then used to get the final anticipated pressure value. The model is able to incorporate the uncertainty and variability in the pressure time series and provide a more reliable forecast of future pressure levels by combining the predictions in this manner. Predicted pressures and the final dataset aggregate are shown in **Figure 5**. Final pressure calculated is 21.17.

A patient's pressure report graph is a graphic depiction of the patient's lung pressure over time. **Figure 6** displays a patient report graph. Plotting a patient's measured lung pressure values against time on a graph result in the creation of this graph. The patient's lung pressure trends and patterns are tracked and analyzed using the pressure report graph, which may then be used to identify and treat any possible lung problems or illnesses. This graph aids healthcare providers in monitoring the efficacy of any therapies given to the patient. The pressure report graph, which offers a thorough perspective of the patient's lung pressure and aids in spotting any unusual patterns or trends that might point to a possible health problem, is a useful tool for medical practitioners.

Figure 7 shows the graph of the relationship between input parameters and the predicted pressure, which is a visual representation of the performance of the deep learning model used for lung pressure prediction. The accuracy of the model is evaluated by comparing the predicted pressure values to the actual measured pressure values, with the deviation between the two shown on the graph. The difference between the predicted pressure values and the actual pressure values is depicted as the discrepancy between the predicted line and the actual pressure line.

Predicted Pressure Array:

```
[ 6.260628   6.0319757  7.0378065  7.711063   8.997519   10.316547
 11.406384  12.518824  13.699374  14.888319  15.905867  16.784061
 17.439693  17.947708  18.846783  19.667286  20.084312  20.703083
 21.35149   21.847557  22.325653  22.777138  23.261406  23.56332
 23.57802   23.662487  23.572319  23.378407  23.32926   23.302334
 23.294819  23.497082  23.477322  23.44869   23.42284   23.39618
 23.363161  23.303679  23.206924  23.162052  23.103111  23.064419
 23.049953  23.007418  22.94349   22.88982   22.839027  22.70842
 22.613007  22.598083  22.623943  22.654438  22.67254   22.68852
 22.718876  22.774462  22.84483   22.922709  23.005184  23.090942
 23.179607  23.271166  23.365519  23.467653  23.608087  23.767906
 23.883541  23.97695   24.061512  24.146725  24.23442   24.323845
 24.416628  24.509819  24.602892  24.70513   24.8171    24.920559
 25.010263  22.906586 ]
```

Final Average Pressure:

```
21.17197992801666
```

Figure 5. Predicted pressure.

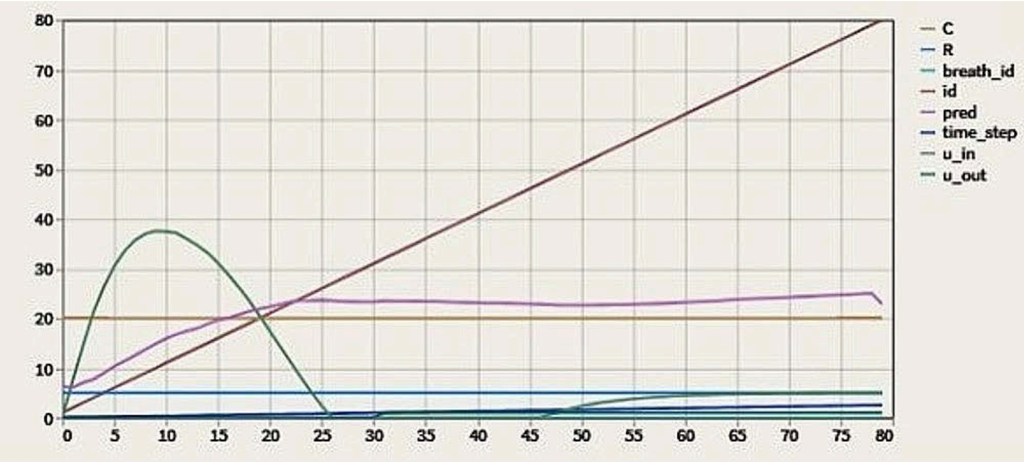

Figure 6. Patient's report.

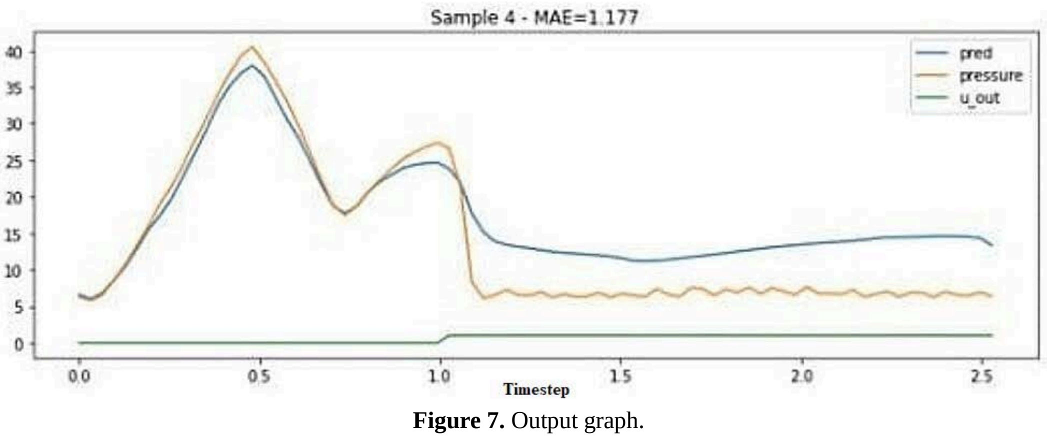

Figure 7. Output graph.

A more efficient model will have a smaller difference between the predicted pressure line and the actual pressure line, indicating that the model's predictions are more accurate and closer to the actual pressure values. Conversely, a larger difference between the predicted line and the actual pressure line indicates that the model's predictions are less accurate and less reliable.

4.1. Comparison of proposed method with existing method

In this section, we present a comprehensive comparison of existing systems for lung pressure prediction. We evaluate and contrast the performance of five regression methods: Linear Regression[21], XGBooster Regression[22], RESNET[23], GRU (Gated Recurrent Unit)[24], and the proposed method based on LSTM**.** We use performance metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage Error (MAPE) for five different regression methods used to predict lung pressure. Comparative table is shown in **Table 1**.

Table 1. Comparison of proposed method with existing method.

Performance metrics	Linear Regression	XGBooster Regression	RESNET	GRU	Proposed method
MSE	3.15	0.15	0.000111	7.23×10^{-7}	1.8523×10^{-7}
RMSE	1.77	0.38	0.0064	0.00083	0.00011
MAE	1.77	0.38	0.005822	0.00071	0.0001
MPE	27	5.8	0.052096	0.00311	0.000246
MAPE	27	5.8	0.087154	0.01049	0.001519

Linear Regression seems to have higher errors (MSE, RMSE, MAE, MPE, MAPE) compared to the other methods. This is expected because Linear Regression assumes a linear relationship between the features and the target variable, which may not be suitable for a complex dataset like lung pressure prediction. XGBooster is an ensemble learning method and generally performs well in various scenarios. It outperforms Linear Regression, but it still has relatively higher errors compared to the deep learning methods (RESNET, GRU, and proposed method).

ResNet is a deep learning architecture known for its ability to handle very deep neural networks. It performs better than Linear Regression and XGBooster in this case, as evidenced by its significantly lower errors. GRU is a type of recurrent neural network (RNN) designed to handle sequential data. It shows an improvement over RESNET in terms of lower errors. Proposed method (LSTM) is another type of recurrent neural network specifically designed to capture long-range dependencies in sequential data. It outperforms all other methods, including GRU, with the lowest errors across all metrics. This suggests that LSTM is the best method for this lung pressure prediction task based on the available data.

LSTM is likely the best method for this lung pressure prediction due to its inherent ability to capture long-range dependencies in sequential data. In the context of lung pressure prediction, the time series data (e.g., lung attributes, control inputs, pressure) likely exhibits temporal patterns and dependencies that affect the lung pressure. LSTM's architecture allows it to learn and retain information over longer time steps, which is crucial for modeling the dynamic behavior of lung pressure. The proposed LSTM method outperforms the standard GRU and other methods by achieving even lower errors. This suggests that the proposed model has been specifically tailored to address the unique characteristics of the lung pressure dataset, making it more accurate in its predictions.

4.2. Future scope

The future use of the deep learning method for predicting lung pressure using LSTM may be broadened in a number of ways. The following are some possible avenues for further work:

1) Increased accuracy: LSTM model accuracy may be further increased by investigating more complex structures, such as attention processes, and by adding more pertinent patient data to the model.

2) Real-time monitoring: the LSTM model may be included into real-time monitoring systems to offer continuous pressure forecasts in real-time, enabling medical personnel to act promptly and with knowledge.

3) Personalized medicine: the LSTM model may be trained using patient-specific data to provide more precise predictions, which may facilitate the creation of therapies that are specifically tailored to the needs of the patient.

4) Integration with other healthcare technologies: to provide healthcare workers a complete solution, the LSTM model may be combined with other healthcare technologies including Electronic Health Records (EHRs) and decision support systems.

The deep learning strategy for lung pressure prediction using LSTM has the potential to transform how medical practitioners monitor and manage patients who are receiving mechanical ventilation, and it has tremendous promise for enhancing the standard of patient care.

5. Conclusion

In treating patients with lung problems, especially in the aftermath of the COVID-19 epidemic that has placed enormous strain on healthcare systems, the prediction of pressure in mechanical ventilation is a crucial component. The research offers a deep learning method based on LSTM to address the pressure prediction problem of sequence prediction. It has been shown that LSTM is superior to a standard RNN at managing these issues. The approach described in the research provided a workable resolution to the problem of pressure prediction in mechanical ventilation and may assist ease the strain on the system's existing support for healthcare. A graph between the input parameters and the expected pressure showed how the final predicted pressure was determined by taking the mean average of the collection of projected pressures. A more effective model was indicated by a lower discrepancy between the pressure and the projected line. Proposed method appears to be the best choice for predicting lung pressure due to its superior performance in terms of lower errors (MSE, RMSE, MAE, MPE, MAPE) compared to the other methods used in the comparison. However, further evaluation and analysis are essential to confirm the robustness and generalizability of the proposed LSTM model. The outcomes of using this strategy show how deep learning has the ability to boost healthcare systems' effectiveness and lighten the load on healthcare professionals.

Author contributions

Methodology and implementation, NPS and RVP; formal analysis, RVP; literature review, data curation and validation, MD and SDK; visualization and validation, PNM and GRS; writing—original draft preparation, NPS and RVP; writing—review and editing, PNM, GRS and SDK. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. Dritsas E, Trigka M. Lung cancer risk prediction with machine learning models. *Big Data and Cognitive Computing* 2022; 6(4): 139. doi: 10.3390/bdcc6040139
2. Sable NP, Wanve O, Singh A, et al. Pressure prediction system in lung circuit using deep learning. In: Choudrie J, Mahalle P, Perumal T, et al. (editors). *ICT with Intelligent Applications.* Springer, Singapore; 2023. Volume 311.
3. Available online: https://ai.googleblog.com/2022/02/machine-learning-for-mechanical.html (accessed on 15 August 2023).

4. Shinde GR, Kalamkar AB, Mahalle PN, et al. Forecasting models for coronavirus disease (COVID-19): A survey of the state-of-the-art. *SN Computer Science* 2020; 1: 1–15. doi: 10.1007/s42979-020-00209-9
5. Hess DR. Respiratory mechanics in mechanically ventilated patients. *Respiratory Care* 2014; 59(11): 1773–1794. doi: 10.4187/respcare.03410
6. Marchuk Y, Magrans R, Sales B, et al. Predicting patient-ventilator asynchronies with hidden Markov models. *Scientific Reports* 2018; 8(1): 17614. doi: 10.1038/s41598-018-36011-0
7. Gunasinghe AD, Aponso AC, Thirimanna H. Early prediction of lung diseases. In: Proceedings of 2019 IEEE 5th International Conference for Convergence in Technology (I2CT); 29–31 March 2019; Bombay, India. pp. 1–4.
8. Oruganti Venkata SS, Koenig A, Pidaparti RM. Mechanical ventilator parameter estimation for lung health through machine learning. *Bioengineering* 2021; 8(5): 60. doi: 10.3390/bioengineering8050060
9. Kulkarni AR, Athavale AM, Sahni A, et al. Deep learning model to predict the need for mechanical ventilation using chest X-ray images in hospitalised patients with COVID-19. *BMJ Innovations* 2021; 7(2): 261–270. doi: 10.1136/bmjinnov-2020-000593
10. Yu L, Halalau A, Dalal B, et al. Machine learning methods to predict mechanical ventilation and mortality in patients with COVID-19. *PLoS One* 2021; 16(4): e0249285. doi: 10.1371/journal.pone.0249285
11. Le S, Pellegrini E, Green-Saxena A, et al. Supervised machine learning for the early prediction of acute respiratory distress syndrome (ARDS). *Journal of Critical Care* 2020; 60: 96–102. doi: 10.1016/j.jcrc.2020.07.019
12. Sayed M, Riano D, Villar J. Predicting duration of mechanical ventilation in acute respiratory distress syndrome using supervised machine learning. *Journal of Clinical Medicine* 2021; 10(17): 3824. doi: 10.3390/jcm10173824
13. Patil RV, Ambritta PN, Mahalle PN, Dey N. Medical cyber—Physical systems in society 5.0: Are we ready? *IEEE Transactions on Technology and Society* 2022; 3(3): 189–198. doi: 10.1109/TTS.2022.3185396
14. Kondo T, Ueno J. Medical image diagnosis of lung cancer by revised GMDH-type neural network using heuristic self-organization. In: Proceedings of SICE Annual Conference 2011; 13–18 September 2011; Tokyo, Japan.
15. Kai J, Fujii F, Shiinoki T. Prediction of lung tumor motion based on recurrent neural network. In: Proceedings of 2018 IEEE International Conference on Mechatronics and Automation (ICMA); 5–8 August 2018; Changchun, China.
16. Olulana K, Owolawi P, Tu C, Abe B. Long thorax disease classification using convolutional long short-term memory. In: Proceedings of 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME); 7–8 October 2021; Mauritius.
17. Agnes SA, Anitha J. Classification of lung nodules using convolutional long short-term neural network. In: Proceedings of 2021 5th International Conference on Computing Methodologies and Communication (ICCMC); 8–10 April 2021; Erode, India.
18. Smagulova K, James AP. A survey on LSTM memristive neural network architectures and applications. *The European Physical Journal Special Topics* 2019; 228(10): 2313–2324. doi: 10.1140/epjst/e2019-900046-x
19. Peoplesvent. Available online: https://www.peoplesvent.org/en/latest/ (accessed on 15 August 2023).
20. Ingmarmed. Available online: https://www.ingmarmed.com/product/quicklung/ (accessed on 15 August 2023).
21. Bersten AD. Measurement of overinflation by multiple linear regression analysis in patients with acute lung injury. *European Respiratory Journal* 1998; 12(3): 526–532. doi: 10.1183/09031936.98.12030526
22. Jiao G, Huang J, Wu B, et al. Association of pulmonary artery pressure change with post-lung transplantation survival: retrospective analysis of China Registry. *JACC: Asia* 2022; 2(7): 819–828. doi: 10.1016/j.jacasi.2022.09.017
23. Angeline R, Vani R. RETRACTED: ResNet: A convolutional Neural Network for detecting and diagnosing of coronavirus pneumonia. In: Proceedings of IOP Conference Series: Materials Science and Engineering; 11–12 December 2020; Tamil Nadu, India.
24. Alam MJ, Rabbi J, Ahamed S. Forecasting pressure of ventilator using a hybrid deep learning model built with Bi-LSTM and Bi-GRU to simulate ventilation. *arXiv* 2023; arXiv:2302.09691. doi: 10.48550/arXiv.2302.09691