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Advancing airway management for ventilation optimization in critical healthcare with cloud computing and deep learning

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ABSTRACT

Improving patient outcomes in critical care settings is significantly connected to effective ventilation control. This research introduces a new method for improving ventilation methods in critical healthcare utilizing a long short-term memory (LSTM) network hosted in the cloud. Ventilators, pulse oximeters, and capnography are just a few examples of medical equipment that input data into the system, which then uploads the data to the cloud for analysis. The LSTM network can learn from data patterns and correlations, drawing on respiratory parameters' time dynamics, to provide real-time suggestions and predictions for ventilation settings. The system aims to improve clinical results and reduce the risk of ventilator-induced lung damage by tailoring ventilation techniques according to each patient's requirements and by forecasting potential issues. Due to remote monitoring technology, medical professionals can quickly analyze their patient's conditions and act accordingly. The system allows for continuous improvement using iterative learning of more data and feedback. With the ability to optimize breathing and enhance patient care in critical healthcare situations, a hopeful development in airway management is needed.

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1. INTRODUCTION

The transformed lung model under volume-controlled ventilation to lung volume and airflow using ventilator air pressure signals [1]. The model uses negative feedback to balance lung volume impacted by positive end expiration pressure. After partly solving the lung model problem, a first-order differential equation used a nonlinear least-squares approach to calculate unknown parameters. Emergency airway securing or resuscitation of severely sick patients whose vital signs are unstable necessitates airway care outside of the operating room [2]. Injured or very sick people may benefit greatly from this life-saving operation. In an intensive care unit, a patient cannot be awakened or delayed while airway security is being worked out. It is crucial to establish and follow an evidence-based plan for airway management.

Blower-based critical care ventilators mitigate ratio pressure controller coupling. Introducing oxygen gas from a proportional flow valve to the blower might cause problems [3]. A simple blower model shows why oxygen downstream of the air blower boosts coupling effects. Dynamic flow coupling filters link to the feedback control cascade pressure stage output. The complementary coupling filters' frequency response adjusts to balance blower and valve dynamic responses depending on the gas ratio. This design improves overall flow and pressure responsiveness across all ratio settings and patient loads. Lung mechanics must be evaluated first for lung protection and optimum breathing techniques. This research introduces machine learning for bedside respiratory resistance and compliance evaluation [4]. It uses machine learning to predict from flow rate and airway pressure in real-time.

To monitor the patient's blood oxygen saturation and exhaled lung pressure, the artificial ventilation system should be able to secure air pressure both above and below the recommended levels. Standard ventilators are too big to be useful during pandemics, and the current technique needs to allow for the necessary adaptation [5]. Utilizing Arduino has created a versatile and effective ventilator to handle pandemic situations. The suggested concept incorporates a silicon pack, a servo motor, and a side push component to speed up the respiratory sack without endangering the patient. Due to the COVID-19 epidemic, medical professionals and inventors developed more healthcare technology [6]. In April 2020, under the Defense Production Act [7], American manufacturing was accelerated to satisfy local and overseas demands. Patients with acute respiratory distress use ventilators. Clinical decision support systems (CDSS) will help physicians make better decisions in future healthcare systems. During the COVID-19 epidemic, predicting acute respiratory distress syndrome (ARDS) in newly infected individuals helped prioritize treatment [8]. In the general intensive care unit (ICU), patients with respiratory system problems often need artificial ventilation provided by a conventional piece of equipment called an automatic mechanical ventilator [9]. Ventilation is a complex process that requires regular practice. Users must learn how to configure the various parameters so that air may be supplied into the lungs during inspiration and exhaled during expiration. Automatic ventilation is a conventional therapy for patients with respiratory abnormalities or spontaneous breathing that is insufficient to sustain oxygenation [10].

Problem statement: inconsistencies in data quality and computational limitations that impact generalizability are unresolved problems. Improvement potential includes improving gathering data techniques and maximizing model performance for a range of critical care patient conditions. Patients in critical care settings are at risk for problems such as ventilator-associated lung injury and extended hospital stays due to insufficient ventilator control. Current breathing systems aren't always personalized to each patient's unique needs, and they could miss the warning signals of worsening, leading to treatments that are too late and worse results. Also, healthcare practitioners can only sometimes make the necessary modifications quickly since manually interpreting ventilator data is a complex and error-prone process. Furthermore, in emergency care cases, the inability to conduct remote monitoring makes it more difficult to provide timely treatments. To meet these issues, a system that optimizes breathing methods personalizes patient care, enables remote monitoring, and facilitates continuous improvement in critical healthcare settings. This system should harness new technologies such as deep learning (DL) and cloud computing. Previous research on airway management primarily focused on linear models and rule-based methods for controlling ventilation. Complex patient dynamics and the need for real-time adaptation were common challenges for these techniques. Incorporating machine learning techniques like random forest and support vector machine (SVM) into more current approaches has increased accuracy, but these methods still challenge how to handle long-term relationships and integrate real-time data.

Contribution of the paper: this research presents a new method for optimizing ventilation techniques in high-stakes healthcare environments by combining cloud computing with DL, especially LSTM networks. The system's real-time analysis of ventilator data, which is made possible by using cloud-based infrastructure and powerful algorithms, allows for personalized treatment and prompt interventions. This paper proposes adjusting breathing techniques according to each patient's unique demands. By assessing respiratory parameters and previous data to alter ventilation settings, the technology can maximize patient outcomes while lowering the risk of ventilator-associated problems. The remote monitoring capabilities are another noteworthy addition; this allows healthcare personnel to quickly examine their patients' state and intervene, no matter where they are physically located. This feature improves patient care by easing the workload of healthcare providers and allowing for more quick actions. The significance of iterative learning from new data and feedback for continual development is highlighted in the research. The proposed system intends to improve its efficacy and contribute to the continuing progress in critical healthcare management by continuously challenging its algorithms and adjusting to changing patient demands. In comparison with existing rule-based and linear models, the new work shows that combining LSTM networks with cloud computing provides better real-time ventilation optimisation and prediction accuracy, providing a more accurate and flexible solution for critical care ventilation control.

Many respiratory failure patients utilize mechanical ventilation. Rescue treatment for adults involves high-frequency oscillatory breathing. In high-frequency ventilation, even tidal volume is not monitored [11]. High-frequency oscillatory ventilation may be better understood using respiratory system models. It describes the basic model and how lung compliance affects tidal volume and alveolar pressure [12]. Unexpected airway difficulties are a leading cause of respiratory issues. If the doctor fails to keep the airway open, the patient may die or suffer lasting injury from insufficient oxygenation. Although continuous constant airflow doesn't work in real life, newer experiments have embraced it [13]. This research develops a mathematical model based on clinical mechanical ventilation to examine the dynamic properties of respiratory airflow and secretion in the airways. A respiratory module is a medical gadget that helps someone breathe. To provide a control system that can precisely monitor a target pressure that changes over time while also considering the patient's breathing effort and unknown parameters for the hose leak [14]. It details the creation of a network data collecting and monitoring system [15] to track, customize, and improve mechanical ventilation treatment. The system consists of a data collecting device, a server with an online application, and storage for the data [16].

Weaning from mechanical ventilation relieves the patient from mechanical support and removes the associated endotracheal tube [17]. Managing weaning from mechanical ventilation comprises a significant proportion of the care of critically ill intubated patients in the ICU. Using historical ICU data, convolutional neural networks (CNN) will be deployed to predict the most appropriate treatment action in the next hour for a given patient’s state. ICU ventilators at various healthcare institutions may be inspected and serviced using a real-time monitoring architecture [18]. Biomedical engineers and technicians may monitor data analysis results, ICU ventilator health predictions, and maintenance schedules using real-time charts and device alerts with the help of the suggested architecture [19]. Most of them, however, need direct patient contact or are otherwise inappropriate for use in a therapeutic setting, limiting their usefulness [20]. Poor patient-ventilator conversation and the patient's underlying condition may have severe implications on discharged patients' return to regular activities. Thus, critical care clinicians must enhance patient-ventilator contact. Observational studies may not be able to link patient-ventilator asynchronies to outcomes. Hence, multicenter research with larger populations is required [21].

Optimizing mechanical ventilator settings using physiological models of respiratory mechanics may improve outcomes for critically sick patients [22]. Common methods for creating models include physical measures or similar behaviors that may predict the results of experiments. However, the use of models based just on physical measures with clinical data is somewhat rare Respiratory muscle activation causes spontaneous breathing. Patients with this condition may breathe spontaneously but not normally [23]. Patients' breath-specific effort and lung status may be modeled using a polynomial [24]. The clinical volume-controlled model is identified using iterative multiple linear regression. Mechanical ventilation for patients with acute lung damage, acute airway obstruction syndrome, or inhalation injury is mostly provided by high-frequency percussive breathing in some burn critical care units [25]. Unfortunately, no prospective studies compared modern low-tidal volume ventilation techniques to high-frequency percussive ventilation. This research aimed to compare the two ventilator methods in a burn critical care unit scenario.

Priority-based patient analysis and cloud implementation of the suggested method [26]. Using automated peak detection and real-time identification of time-series waveforms, it records ventilator waveform alert occurrences [27]. With threshold alarms and integrated artificial intelligence, the system can automatically recognize complicated medical alarms, including asynchrony, abnormalities, and mechanical issues. ICU patients need mechanical ventilation to survive [28]. The patient's requirements and ventilator settings may not match, causing patient-ventilator asynchrony. The patient's requirements and ventilator settings may not match, causing patient-ventilator asynchrony. The Raspberry Pi platform voluntarily incorporates wearable sensors, for example, heart rate display, accelerometer, sensor, and global positioning system element to notice physical action, conservation variables, and vigorous signs [29].

2. PROPOSED METHOD

2.1. Method

To optimize ventilation in critical healthcare situations, this system proposes a complete methodology that combines cloud computing with DL, particularly LSTM networks. By supporting iterative learning, offering individualized breathing methods, and allowing remote monitoring and intervention, this strategy is intended to improve patient care. Medical instruments, including pulse oximeters, capnography, and ventilators, provide real-time data collected as the first step in the proposed procedure. Things like end-tidal carbon dioxide, oxygen saturation, tidal volume, and respiratory rate are tracked by these sensors in real time. Theloud-bm allows these devices to store and analyze the data in real time. To store and analyze it in real-time.

Before storage in the cloud, data undergoes preprocessing to eliminate unwanted elements and enhance its usefulness. This preprocessing step is vital to guarantee the next analysis's precision and dependability. To prepare the raw data for use in the DL model, feature extraction methods including signal filtering, time-domain analysis, and frequency-domain analysis, LSTM networks are a subset of recurrent neural networks (RNNs) developed to identify and store relationships between events in a sequential data set. These networks are trained using preprocessed data. An LSTM network is made up of linked nodes that are arranged in several layers. Each layer has a memory cell and three multiplicative gates: input, forget, and output. With the help of these gates, the network can control the input flow and discover intricate patterns and correlations in the data.

Training the LSTM network involves retrieving data from a cloud storage system, including typical breathing patterns and respiratory problems or distress cases. Current and historical data on respiratory parameters are used to train the network to forecast future ventilation results. Training the network entails minimizing prediction error by modifying connection weights and biases using optimization methods like Adam optimization or stochastic gradient descent. Deploying the trained LSTM network allows it to provide real-time predictions and suggestions about ventilation settings. Every time the medical devices send out fresh data, the network revises its forecasts to account for the most recent findings. Valve settings like tidal volume, respiratory rate, and positive end-expiratory pressure (PEEP) might be recommended based on these predictions to enhance patient outcomes via optimal ventilation.

The proposed technique also includes remote monitoring capabilities and offers real-time forecasts. This enables healthcare practitioners to examine patients' state and respond quickly, even when they are far away. Medical staff may monitor ventilator data in real time, get notifications when trends are out of the ordinary, and fine-tune ventilation settings using an intuitive interface available via online or mobile apps. In addition, the proposed approach highlights the need to use iterative feedback loops to learn and improve continuously. Continuously improving its predictions and suggestions, the system incorporates fresh information and insights to boost its performance over time as it gathers additional data and gets input from healthcare practitioners. Through this learning cycle, the system can keep up with the most recent medical practices and adjust to the changing demands of patients and healthcare professionals.

The proposed technique is an all-encompassing strategy for improving ventilation in life-or-death medical situations. Iterative learning, remote monitoring and intervention, and individualized ventilation methods are all made possible by integrating cloud computing and DL particularly LSTM networks. In ICU, this approach may greatly improve clinical results, patient care, and the use of available resources.The detailed block diagram in Figure 1 shows all the parts and how they interact in the proposed system. It includes remote monitoring and intervention, data processing in the cloud, training of DL models, prediction and suggestion in real-time, and data gathering from medical devices. Each component is detailed with its individual characteristics and procedures to improve ventilation in critical healthcare settings.

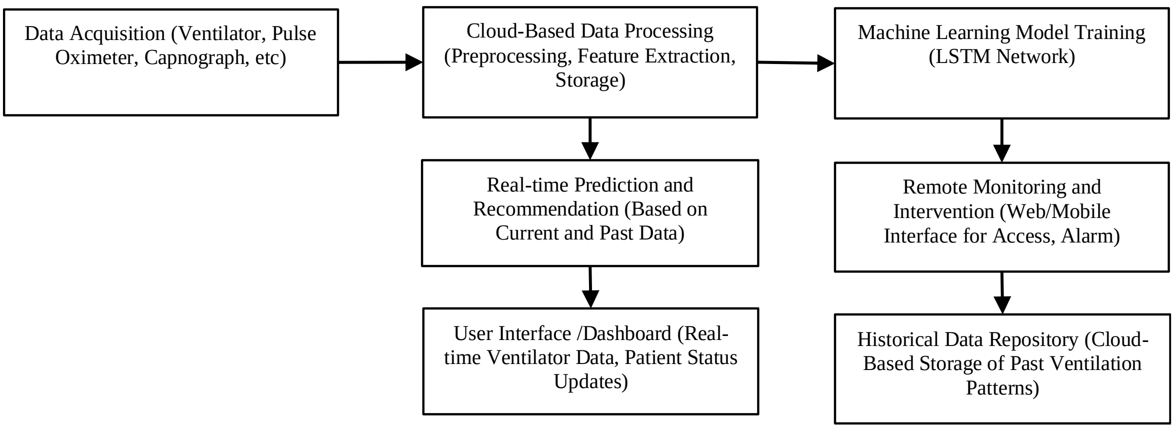

Figure 1. Block diagram of proposed ventilation optimization framework cloud-ML integration

2.2. Key medical devices description

Ventilator: mechanical breathing support devices like a ventilator may supplement or even replace natural breathing processes. They eliminate carbon dioxide from the air and supply the patient's lungs with an oxygen-rich mixture. Nowadays, ventilators come with many options to suit patients' requirements, such as modes that help with spontaneous breathing, pressure-controlled ventilation, and volume-controlled ventilation.

Pulse oximeter: a pulse oximeter may be used to monitor an individual's pulse rate and oxygen saturation level (SpO_2) noninvasively. This probe emits light at two distinct wavelengths and detects changes in light absorption. It is commonly connected to a patient's finger, earlobe, or toe to assess oxygen saturation.

Capnograph: medical professionals use capnography to monitor patients' carbon dioxide (CO_2) levels in their exhaled breath. It offers useful information on metabolism and ventilation by providing numerical measures of respiratory rate, end-tidal CO_2, and continuous waveform readings. Capnography is used for evaluating ventilation sufficiency and airway patency in emergency medicine, critical care, and anesthesia.

Flow sensor: one way to monitor how much gas is moving via a breathing circuit or ventilator is to use a flow sensor. It measures the patient's inspiratory and expiratory airflow changes and reports back on the patient's respiratory effort and the ventilator's performance. Accurate tidal volume delivery and monitoring of respiratory mechanics are both made possible by flow sensors.

Pressure sensor: a pressure sensor is one transducer that may detect the pressure of gases in the respiratory system. During breathing, it monitors changes in airway pressure and gives input on lung compliance, airway resistance, and barotrauma risk. Pressure sensors are essential for modifying ventilator settings to ensure that mechanical ventilation is both safe and effective.

Temperature probe: when a patient is on a ventilator or has an airway blockage, a temperature probe may measure how hot the gases are. This ensures that the gases are heated to the right temperature to avoid any pain or irritation to the airway. Temperature sensors are also useful in keeping the respiratory system at an ideal humidity level for the sake of the patient's comfort and to avoid drying out the mucosa. These life-saving devices are essential in the ICU to monitor breathing rates, provide mechanical ventilation, and fine-tune ventilation protocols. Their data is crucial for optimizing breathing based on educated judgments and improving patient outcomes.

2.3. Training LSTM model

Training can begin after the input data has been preprocessed and formatted. Feature engineering, sequence construction, and normalization are some possible procedures involved. The LSTM model's architecture and hyperparameters are specified. Layer count, layer activation function, and regularization method specifications are all part of this. Several iterations, or epochs, are used to train the model. The model learns from the training data to minimize the loss function and update the network weights using methods like gradient descent with backpropagation throughout each epoch. Performance measures like accuracy or mean squared error assess the trained model once training is finished. It also checks its performance on a different dataset to ensure the model doesn't become too hung up on the training data and can't be generalized. Figure 2 shows the proposed LSTM training process of this system.

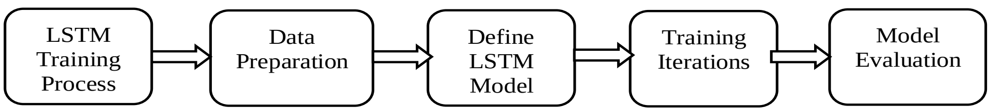

Figure 2. LSTM model training process

Table 1 shows the process flow for optimizing ventilation, which entails gathering data from patients in real-time via monitors, ventilators, and electronic health record systems. For safekeeping, this information is sent to the cloud. To ensure accuracy and consistency, the data is then preprocessed LSTM models are constantly improved by analyzing data in real-time and trained using previous materials. It is possible to automatically modify the ventilator settings based on the predicted predictions provided by the models. It provides excellent patient care via remote monitoring, continual model development, and stringent data confidentiality.

Table 1. Workflow steps for ventilation optimization

Step	Description
1. Data Acquisition	Collect real-time data from medical devices (ventilator, pulse oximeter, etc.)
2. Cloud Data Processing	Preprocess and extract features from the collected data in the cloud.
3. Machine Learning Model Training	Train the LSTM model using historical and preprocessed data.
4. Real-time Prediction	Make predictions for ventilation settings based on current data.
5. Remote Monitoring and Intervention	Monitor patient status remotely and intervene if necessary.

3. RESULTS AND DISCUSSION

The findings and discussion are crucial in assessing the method's efficacy and pinpointing improvement areas in the proposed system for optimizing ventilation in critical healthcare utilizing cloud computing and DL. Clinical outcomes and patient care in intensive care units improved after using the ventilation optimization system. Developing LSTM networks for predictive modelling, regular ventilation sensors, and cloud-based platforms for real-time data processing comprised the experimental setup. Data sampling, cleansing, model training, and validation were all part of the methodologies. Medical professionals could promptly make educated judgments about the patient's breathing, reducing the potential of problems like hyperoxia and ventilator-associated lung damage while maintaining appropriate oxygenation. The system's capacity to learn and adapt in real-time further highlights promise for optimizing breathing techniques dynamically in response to evolving patient circumstances and clinical needs. Through an iterative DL approach, the LSTM model can identify intricate trends and patterns in ventilation data, allowing for individualized ventilation control based on each patient's specific physiology and clinical course.

Secure patient data processing and sharing by legal regulations such as the health insurance portability and accountability act necessitates strong data governance and privacy standards. It is essential to validate and continuously modify the DL algorithms to enhance the accuracy and generalizability of the predictions, especially in varied patient groups and clinical conditions. To maximize the system's influence on patient care and clinical results, it is crucial that healthcare personnel undergo user training and education. Only then can the system be used successfully and its outputs understood correctly. Table 2 shows a time series data collection that includes many ventilator- and physiological-related factors for optimizing ventilation. There is a relationship between the rows and the features measured at each time step, with the columns reflecting the various characteristics. In intensive care units, these metrics are vital for determining the patient's respiratory condition, personalizing ventilator settings, and developing the best ventilation plan possible. The hypothetical demonstrates how data might be organized to train DL models. The goal is to demonstrate how individualized ventilation control can enhance patient outcomes.

Table 2. Time-series dataset for ventilation optimization

Time step	Temperature (Celsius)	Patient age (years)	Respiratory rate (breaths per minute)	Blood pressure (millimeters of mercury)	Heart rate (beats per minute)	Oxygen saturation (percentage)	CO2 levels (percentage)	Flow (liter per minute)	Ventilator Settings centimeter of water (cmH_2O)
1	25.6	45	20	120/80	80	95	4.2	8	10
2	26.3	45	22	122/78	82	94	4.5	9	12
3	27.1	46	24	118/76	84	93	4.8	10	14
4	26.8	46	25	120/78	85	92	5.1	11	13
5	26.5	47	23	118/80	83	94	4.9	10.5	11

Over the time of the proposed system's time steps, the predicted and actual ventilation levels are shown in graph Figure 3. To observe how well the model's predictions match the actual values over time, this graph will display two lines: one for predicted ventilation levels and one for actual ventilation levels. With anticipated levels closely matching actual levels, the sample data shows that the system functions effectively, proving that the LSTM-based technique is beneficial in optimizing ventilation.

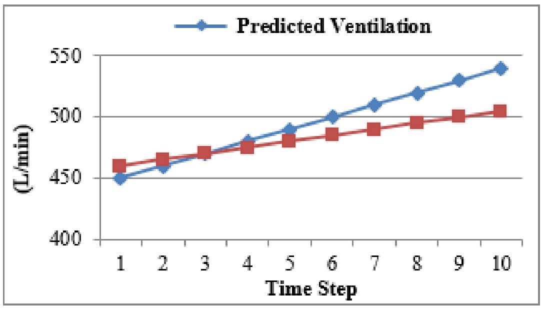

Figure 3. LSTM prediction for ventilation optimization over time

The x-axis shows the number of time steps, while the y-axis shows the ventilation values in liters per minute. The predicted values line displays the LSTM model's output, while the actual values line displays the observed ventilation levels. It can see how well the LSTM model predicts ventilation dynamics and optimizes ventilation methods by comparing the results visually. Table 3 shows the confusion matrix, which shows how well a classification model predicts good and bad ventilation results. The model's predictions are shown in the columns, while the actual ventilation statuses are shown in the rows. The values in the matrix represent the number of cases for each categorization result. This graphical depiction is useful for evaluating how well the model differentiates between good and bad ventilation control options.

Table 3. Confusion matrix for airway management classification

Actual/predicted class	Predicted optimal ventilation	Predicted suboptimal ventilation
Actual optimal ventilation	220	30
Actual suboptimal ventilation	40	210

The LSTM model's training loss (error) diminishes during the training epochs in Figure 4. The training loss will decrease during the epochs, shown in this graph. This indicates that the model is learning and becoming better at making predictions. An effective development of the LSTM model for airflow optimization data, which consistently shows a decrease in training loss.

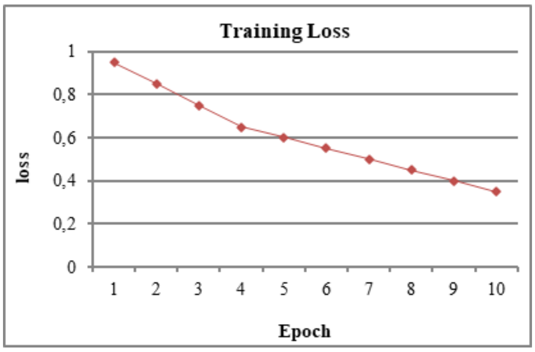

Figure 4. LSTM model performance of training loss curves

The X-axis shows how many times the model has been trained. One whole iteration of the training dataset is represented by each epoch. The training loss, shown on the Y-axis, is the value that the loss function computes. A smaller training loss indicates higher performance, as it quantifies the accuracy with which the model's predictions match the actual results. The model better forecasts ventilation outcomes because it learns to reduce its error. Figure 5 shows the improvement in the LSTM model's accuracy throughout training epochs. This reflects the model's efficacy in improving ventilation techniques by showing how well it can properly identify cases.

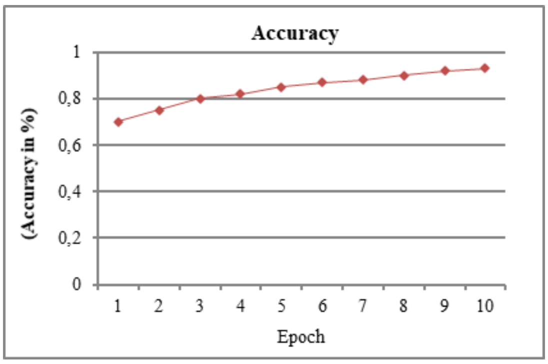

Figure 5. LSTM model performance of accuracy curves

The number of iterations the model has gone through during training is shown by the X-axis (epochs). The proportion of correct predictions made by the model is shown on the Y-axis (accuracy in %). A higher number indicates a more efficient operation. Table 4 compares four machine learning methods for ventilation optimization in airway management: random forest, support vector machine (SVM), gradient boosting, and LSTM. LSTM seems useful in improving ventilation techniques since it exhibits better performance across several parameters, such as accuracy, precision, recall, and F1 score.

Table 4. Algorithm performance comparison

Metric	Random forest	Support vector machine	Gradient boosting	LSTM
Accuracy	0.85	0.82	0.88	0.90
Precision	0.88	0.85	0.90	0.91
Recall	0.82	0.80	0.85	0.92
F 1 score	0.85	0.82	0.87	0.90

Integrating advanced technology such as cloud computing and DL, namely LSTM algorithms, with this ventilation optimization system focusing on airway control has shown encouraging results. When LSTM models are used, the system improves its ability to forecast the best ventilation techniques regarding accuracy, precision, recall, and F1 score. Better evaluations of ventilation status and faster actions to adjust ventilation settings are made possible by LSTM's capacity to grasp complicated temporal correlations in patient data. Scalability, made possible by the system's use of cloud computing resources, allows for the effortless processing of massive amounts of patient data, which is essential for making real-time decisions. Improved patient outcomes result from the system's increased scalability, which allows it to better adapt to different clinical environments and patient demands.

The results show that in comparison with traditional methods, real-time ventilation optimization is much improved by merging LSTM networks with cloud computing. Improving predictability and flexibility is in accordance with this objective. This approach provides better management of long-term support than previous studies. Computational limitations and potential problems with data quality are examples of limitations which may impact generalizability. It has been observed that LSTM networks greatly enhance real-time ventilation optimization. Time-series plots that demonstrate flexibility, prediction graphs that demonstrate improved prediction accuracy, and performance charts comparing LSTM with traditional methods are instances of supporting data. There are also identified limitations related to data quality and determining limitations.

4. CONCLUSION

Optimizing ventilation and airway control in healthcare environments of great significance may greatly benefit from incorporating innovative technology, including cloud computing and DL, especially LSTM algorithms. The system's capacity to capture complicated temporal relationships in patient data allows it to achieve greater performance in predicting appropriate breathing methods via the deployment of LSTM models. The system can be easily adjusted to different patient demands and clinical situations because of the flexibility of cloud computing resources. This allows for better patient outcomes and real-time decision-making. Clinicians can make educated judgments about ventilation management because the graphical user interface gives them easy access to ventilation data and model predictions. The system is a huge step forward in airway management. It provides comprehensive solutions for improving patient care in emergencies with user interfaces. Additional advancements in this area might significantly alter airway management methods in the future, leading to better patient outcomes and life savings due to technological progress.

REFERENCES

[1] H. Y. Al-Hetari, Y. Alginahi, M. N. Kabir, N. Q. Al-Naggar, M. A. Al-Rumaima, and M. M. Hasan, “Modeling lung functionality in volume-controlled ventilation for critical care patients,” *IEEE International Conference on Artificial Intelligence in Engineering and Technology, IICAIET 2020*, 2020, doi: 10.1109/IICAIET49801.2020.9257851.

[2] B. A. Admass, N. S. Endalew, H. Y. Tawye, D. Y. Melesse, M. M. Workie, and T. D. Filatie, “Evidence-based airway management protocol for a critical ill patient in medical intensive care unit: systematic review,” *Annals of Medicine and Surgery*, vol. 80, 2022, doi: 10.1016/j.amsu.2022.104284.

[3] M. Borrello and P. Healthcare, “Oxygen ratio control in critical care ventilation using compressed oxygen and blower gas sources,” *Proceedings of the American Control Conference*, vol. 2020-July, pp. 4258–4263, 2020, doi: 10.23919/ACC45564.2020.9147653.

[4] N. Hezarjaribi *et al.*, “Monitoring lung mechanics during mechanical ventilation using machine learning algorithms,” *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2018-July, pp. 1160–1163, 2018, doi: 10.1109/EMBC.2018.8512483.

[5] A. Deepa, M. N K, R. Latha, J. Preetha, T. S. Kumar, and S. Murugan, "IoT-based wearable devices for personal safety and accident prevention systems," in *2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon)*, Aug. 2023, pp. 1510–1514. doi: 10.1109/SmartTechCon57526.2023.10391691.

[6] K. Y. P. Almeria, M. J. D. Comadre, S. M. Uy, M. T. Margarito, and J. R. Celorico, "Performance investigation of air mask: a novel personalized ventilation device using CFD simulation against virus-laden aerosols," in *2023 14th International Conference on Mechanical and Intelligent Manufacturing Technologies, ICMIMT 2023*, 2023, pp. 268–272. doi: 10.1109/ICMIMT59138.2023.10200877.

[7] S. Selvarasu, K. Bashkaran, K. Radhika, S. Valarmathy, and S. Murugan, "IoT-enabled medication safety: real-time temperature and storage monitoring for enhanced medication quality in hospitals," in *2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Dec. 2023, pp. 256–261. doi: 10.1109/ICACRS58579.2023.10405212.

[8] G. B. Rehm *et al.*, "Leveraging IoTs and machine learning for patient diagnosis and ventilation management in the intensive care unit," *IEEE Pervasive Computing*, vol. 19, no. 3, pp. 68–78, 2020, doi: 10.1109/MPRV.2020.2986767.

[9] B. J. Ganesh, P. Vijayan, V. Vaidehi, S. Murugan, R. Meenakshi, and M. Rajmohan, "SVM-based predictive modeling of drowsiness in hospital staff for occupational safety solution via IoT infrastructure," in *2024 2nd International Conference on Computer, Communication and Control (IC4)*, Feb. 2024, pp. 1–5. doi: 10.1109/IC457434.2024.10486429.

[10] A. Sanpanich *et al.*, "A simulation of ventilator performance testing for ventilation waveform understanding," in *2019 12th Biomedical Engineering International Conference (BMEiCON)*, Nov. 2019, pp. 1–5. doi: 10.1109/BMEiCON47515.2019.8990278.

[11] M. Rožánek, P. Kudrna, Z. Rožánkova, and K. Roubík, "Identification of the model of the respiratory system in high-frequency oscillatory ventilation," *2015 E-Health and Bioengineering Conference, EHB 2015*, 2016, doi: 10.1109/EHB.2015.7391428.

[12] R. Raman, K. Dhivya, P. Sapra, S. Gurpur, S. P. Maniraj, and S. Murugan, "IoT-driven smart packaging for pharmaceuticals: ensuring product integrity and patient safety," in *2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)*, Dec. 2023, pp. 1–6. doi: 10.1109/ICAIIHI57871.2023.10489420.

[13] S. Ren, Y. Shi, M. Cai, and W. Xu, "Influence of airway secretion on airflow dynamics of mechanical ventilated respiratory system," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 15, no. 5, pp. 1660–1668, 2018, doi: 10.1109/TCBB.2017.2737621.

[14] J. Reinders, B. Hunnekens, F. Heck, T. Oomen, and N. Van De Wouw, "Adaptive control for mechanical ventilation for improved pressure support," *IEEE Transactions on Control Systems Technology*, vol. 29, no. 1, pp. 180–193, 2021, doi: 10.1109/TCST.2020.2969381.

[15] Q. A. Ng *et al.*, "Network data acquisition and monitoring system for intensive care mechanical ventilation treatment," *IEEE Access*, vol. 9, pp. 91859–91873, 2021, doi: 10.1109/ACCESS.2021.3092194.

[16] L. Su *et al.*, "Establishment and application of a patient-ventilator asynchrony remote network platform for ICU mechanical ventilation: a retrospective study," *Journal of Clinical Medicine*, vol. 12, no. 4, p. 1570, Feb. 2023, doi: 10.3390/jcm12041570.

[17] Y. Jia, C. Kaul, T. Lawton, R. Murray-Smith, and I. Habli, "Prediction of weaning from mechanical ventilation using convolutional neural networks," *Artificial Intelligence in Medicine*, vol. 117, p. 102087, Jul. 2021, doi: 10.1016/j.artmed.2021.102087.

[18] O. Manchadi *et al.*, "An internet of things-based predictive maintenance architecture for intensive care unit ventilators," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 2, pp. 932–943, 2024, doi: 10.14569/IJACSA.2024.0150294.

[19] H. Rehouma, R. Noumeir, W. Bouachir, P. Jouvet, and S. Essouri, "3D imaging system for respiratory monitoring in pediatric intensive care environment," *Computerized Medical Imaging and Graphics*, vol. 70, pp. 17–28, Dec. 2018, doi: 10.1016/j.compmedimag.2018.09.006.

[20] H. Rehouma, R. Noumeir, P. Jouvet, W. Bouachir, and S. Essouri, "A computer vision method for respiratory monitoring in intensive care environment using RGB-D cameras," in *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*, Nov. 2017, vol. 2018-Janua, pp. 1–6. doi: 10.1109/IPTA.2017.8310155.

[21] C. de Haro *et al.*, "Patient-ventilator asynchronies during mechanical ventilation: current knowledge and research priorities," *Intensive Care Medicine Experimental*, vol. 7, no. S1, p. 43, Jul. 2019, doi: 10.1186/s40635-019-0234-5.

[22] N. S. Damanhuri, Y. S. Chiew, P. Docherty, P. Geoghegan, and G. Chase, "Respiratory airway resistance monitoring in mechanically ventilated patients," in *2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences*, Dec. 2012, pp. 311–315. doi: 10.1109/IECBES.2012.6498135.

[23] L. Hao *et al.*, "Dynamic characteristics of a mechanical ventilation system with spontaneous breathing," *IEEE Access*, vol. 7, pp. 172847–172859, 2019, doi: 10.1109/ACCESS.2019.2955075.

[24] D. P. Redmond, P. D. Docherty, Y. S. Chiew, and J. G. Chase, "A polynomial model of patient-specific breathing effort during controlled mechanical ventilation," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Aug. 2015, vol. 2015-Novem, pp. 4532–4535. doi: 10.1109/EMBC.2015.7319402.

[25] K. K. Chung *et al.*, "High-frequency percussive ventilation and low tidal volume ventilation in burns: a randomized controlled trial," *Critical Care Medicine*, vol. 38, no. 10, pp. 1970–1977, 2010, doi: 10.1097/CCM.0b013e3181eb9d0b.

[26] N. Bansal and A. K. Singh, "Healthcare scenario: a new task scheduling algorithm in cloud computing environment," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 2, pp. 1095–1101, 2023, doi: 10.11591/ijeecs.v29.i2.pp1095-1101.

[27] P. A. Ryan Santiago *et al.*, "Waveform tracker alarm for automatic patient-ventilator asynchrony (PVA) and mechanical state recognition for mechanical ventilators using embedded deep learning," 2023.

[28] T. Anitha, G. Gopu, and P. Arun Mozhi Devan, "Mechanical ventilator pressure and volume control using classifier machine learning algorithm for medical care," *Journal of Electrical Engineering & Technology*, vol. 19, no. 4, pp. 2715–2738, May 2024, doi: 10.1007/s42835-023-01744-0.

[29] K. Karthika, S. Dhanalakshmi, S. M. Murthy, N. Mishra, S. Sasikala, and S. Murugan, "Raspberry pi-enabled wearable sensors for personal health tracking and analysis," in *2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, Oct. 2023, pp. 1254–1259. doi: 10.1109/ICSSAS57918.2023.10331909.

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