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Advancing ICU patient care with a Real-Time predictive model for mechanical Power to mitigate VILI

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ABSTRACT

Background: Invasive Mechanical Ventilation (IMV) in Intensive Care Units (ICU) significantly increases the risk of Ventilator-Induced Lung Injury (VILI), necessitating careful management of mechanical power (MP). This study aims to develop a real-time predictive model of MP utilizing Artificial Intelligence to mitigate VILI.
Methodology: A retrospective observational study was conducted, extracting patient data from Clinical Information Systems from 2018 to 2022. Patients over 18 years old with more than 6 h of IMV were selected. Continuous data on IMV variables, laboratory data, monitoring, procedures, demographic data, type of admission, reason for admission, and APACHE II at admission were extracted. The variables with the highest correlation to MP were used for prediction and IMV data was grouped in 15-minute intervals using the mean. A mixed neural network model was developed to forecast MP 15 min in advance, using IMV data from 6 h before the prediction and current patient status. The model's ability to predict future MP was analyzed and compared to a baseline model predicting the future value of MP as equal to the current value.
Results: The cohort consisted of 1967 patients after applying inclusion criteria, with a median age of 63 years and 66.9 % male. The deep learning model achieved a mean squared error of 2.79 in the test set, indicating a 20 % improvement over the baseline model. It demonstrated high accuracy (94 %) in predicting whether MP would exceed a critical threshold of 18 J/min, which correlates with increased mortality. The integration of this model into a web platform allows clinicians real-time access to MP predictions, facilitating timely adjustments to ventilation settings.
Conclusions: The study successfully developed and integrated in clinical practice a predictive model for MP. This model will assist clinicians allowing for the adjustment of ventilatory parameters before lung damage occurs.

1. Introduction

IMV has saved many lives since its inception. However, it is not without adverse events, such as VILI[1].

VILI has been extensively studied over the years. It began with barotrauma [2] aused by elevated airway pressures, followed by volutrauma[3,4] caused by excessive Vt, and atelectrauma [5,6] caused by the continuous opening and closing of the alveoli. In 2016, Gattinoni et al.[7] introduced the term ergotrauma [8] as the lung damage caused by the amount of energy applied to the lung per unit of time (J/min), termed mechanical power.

Since Gattinoni et al. postulated MP as a parameter to monitor in IMV [7], advocating that it combines all components that have been demonstrated to produce VILI (plateau pressure[9,10], driving pressure [11], PEEP[12], TV [3,4], respiratory rate [13], and flow[14,15]), many studies have been conducted to analyze its relationship with outcomes in ventilated critical patients. Most of these studies have found that higher MPs are associated with more lung damage, higher mortality, more days on IMV, and longer ICU stays [16–24].

In recent years, AI and predictive models in medicine have gained momentum, primarily due to the large databases generated from continuous monitoring and extraction of such data from CIS [25,26].

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Most of these models in ICUs have been created with the intention of predicting mortality [27–29] or days on IMV [30], with most of these models having an acceptable AUC-ROC.

In this context, it would be interesting to develop a predictive model of MP that could alert the clinician that their patient is going to exceed safe MP limits, so they could modify ventilator parameters to prevent VILI.

2. Objective

To create and validate a real-time predictive model of MP through CIS and implement the predictive model on a web platform for use by clinicians.

3. Materials and methods

A retrospective observational study was conducted in a 28-bed multidisciplinary ICU of a tertiary university hospital from January 2018 to May 2022. Patients over 18 years old who were admitted to the ICU and received invasive mechanical ventilation (IMV) for more than 6 h at any time during their stay were included in the study.

3.1. Outcome

The variable to be predicted is the MP 15 min in advance. For its prediction, IMV data from the previous 6 h as well as variables describing the patient's critical state at that time were used.

MP was calculated using the following formula [7]:

$$MP = 0.098 \times RR \times Vt \times (Ppeak - (DP/2))$$

where MP = Mechanical Power, RR = Respiratory Rate, Vt = Tidal Volume, DP = Driving Pressure, defined as Plateau Pressure − PEEP, and Ppeak = Peak Pressure.

3.2. Data extraction and collection

The CIS data used are stored in the hospital's Data Warehouse. To extract the relevant variables, an Extraction, Transformation, and Loading process was implemented in SQL via Python [25,31].

Static data was extracted for all patients, including their entry and exit times, demographic data, the type of admission (urgent or elective), the reason for admission according to the criteria established by SEMICYUC (Spanish Society of Intensive Medicine and Coronary Units) [31] and the APACHE II [32] score. This static data was collected by the clinicians during the patient stay and directly inserted at the SIC as electronic health records.

Finally, variables related to IMV, laboratory data, monitoring data, and procedural data were continuously extracted at the ICU only for those patients with IMV. For each variable we extracted the numerical values and the time this value was reported. IMV and monitoring data were continuously collected through clinical devices at bedside and sent straight to the SIC. The IMV variables needed to calculate the MP were automatically transferred from the ventilator to the CIS every two minutes. The respirator transferred the RR, TV, PEEP, peak pressure, and plateau pressure directly; DPs were calculated by subtracting the PEEP from the Plateau Pressure. MP were only calculated when all the components of the formula where available. Plateau Pressure values were obtained only when patients were in controlled modes and the percentage of inspiratory pause was > o = 10 % of the respiratory cycle. These variables had a granularity ranging from 2 to 15 min. Laboratory data was collected via laboratory information system once a day for patients that need it. Procedural data was reported by clinicians into the SIC as electronic health records whenever a procedure was realized in a patient.

3.3. Data Transformation

To facilitate better handling of continuous data, we created 15-minute time windows from patient admission to discharge. For each continuous variable, the average for each 15-minute window was calculated. For each MP prediction, data from the last 6 h of ventilation were used, equivalent to the 24 preceding time windows. Only time windows in which the patient had remained the previous 6 h under controlled mechanical ventilation with MP values recorded during that entire time and had a MP value to predict in the next 15 min were included.

We then selected variables for MP prediction using a Pearson correlation test. Variables with higher correlation were assigned to a group of temporal variables, which were used temporally in the model, primarily composed of IMV variables. Other variables with correlation were assigned to a group that would only contribute their last value to the model, defining the critical state of the patient. Details of selected variables and their correlations are available in Appendix A.

Subsequently, we eliminated outlier values for the variables in the temporal group used for MP calculation, and missing data were completed. The outlier values were defined clinically, and the specifics of the extreme values defined, and the missing data filling are stated in the Appendix B. We did not search for outlier values in the group of variables defining the critical state of the patient.

Additionally, temporal variables were derived with the aim of enriching the information provided to the data model. These derived variables are only related to variables in the IMV variables group and are focused on capture the context of the actual values and the interactions between IMV variables. The definition and selection of the two groups of new derived variables that aim to capture context and interactions of the MV variables is explained in Appendix C.

All data processing was carried out using the Pandas, scikit-learn, scipy, and numpy libraries in Python.

3.4. Division into Training/Test sets

Patients were divided into two sets: training 80 % and validation 20 %. All temporal windows of a patient were assigned to the same set to prevent information leakage.

Standardization of all variables was performed after the division into sets to prevent possible data leakage from the test set to the train set.

3.5. Model development

The model developed for MP prediction is a mixed neural network model combining LSTM layers and artificial layers. The LSTM layers receive as input 54 temporal variables over 24 time windows, while the artificial layers receive the patient's critical state at the time of prediction.

Subsequently, both parts of the model are concatenated for final processing and to generate an MP prediction for the next 15 min. The model representation the specifics of training can be found in Appendix D.

To evaluate the results, we analyze the model's capacity to numerically predict MP. Besides this, an MP threshold is established to categorize predictions as "good- future MP" or "bad-future MP". The model's usefulness in both categories and its ability to predict changes between them is examined.

To have a reference point to evaluate the model's performance, it is compared with a baseline model that always predicts that the future MP value will be the same as the current value.

3.6. Implementation of the predictive model in clinical practice

For the real-time integration of the developed model, a web platform for IMV was created, allowing real-time data visualization of patients in the ICU. The entire process of data extraction, processing, window selection and MP prediction were integrated into a single pipeline with Django and Python. The platform enables clinicians to visualize the state of IMV graphically in the ICU, including MP forecasts.

Clinicians can access the web platform through a web server located in the hospital, and the entire web platform is containerized in Docker with a Nginx intermediate layer to protect against potential unauthorized access attempts.

4. Results

4.1. Description of the cohort

A total of 4079 patients were admitted during the study period. After applying the inclusion criteria, the cohort was reduced to 1967 patients. Of the 1967 patients who had at least one MV window, the median age was 63 years [range 51–71], and 66.9 % were male. The mortality rate was 30 %, and the median MP was 16 J/min. Nominal characteristics of the cohort are presented in Table 1. Description of continuous data used in our model is at Table 2.

In total, 2,969,873 15-minute windows were recorded, of which 1,203,459 were used to train the model as they corresponded to controlled modalities.

4.2. Baseline model

Initially, a baseline model was developed to compare the results of our Deep Learning model. This model has a Mean Squared Error (MSE) of 3.47, a Root MSE (RMSE) of 1.86 and a Mean Absolute Error (MAE) of 0.93. Different predictions of the baseline model over a 6-hour period can be observed in Fig. 1.

Furthermore, to evaluate how the model behaves in the face of large changes in MP, the mean squared error was analyzed in all those IMV windows where the change in 15 min exceeded 2 MP points. A MSE of 24.59 was obtained in these predictions, along with a RMSE of 4.96 and a MAE o 4.10. This indicates that predicting the current value as the next MP value is erroneous because significant errors are made when the MP experiences significant changes.

4.3. Deep learning model

The trained Deep Learning model presents a MSE of 2.79 in the test set, a RMSE of 1.66 and a MAE of 0.88, representing a 20 % improvement in MSE compared to the baseline model for all MP predictions. Additionally, for moments when there is a change of more than 2 points in MP, the MSE is 18.18, the RMSE is 4.26 and the MAE is 3.48. These results demonstrate that our model can predict MP more accurately in 15 min than the baseline model, especially in moments of significant changes.

Table 1
Nominal characteristics of the population.

Variable	Categories	Missings	Values
n			1967
Gender, n (%)	F	0	652 (33.1)
Gender, n (%)	M		1315 (66.9)
ICU Discharge, n (%)	Domicile	0	10 (0.5)
ICU Discharge, n (%)	Exitus		600 (30.5)
ICU Discharge, n (%)	OH		119 (6.0)
ICU Discharge, n (%)	Ward		1238 (62.9)
Source of admission, n (%)	0	0	4 (0.2)
Source of admission, n (%)	ER	0	705 (35.8)
Source of admission, n (%)	OH	0	328 (16.7)
Source of admission, n (%)	OR	0	442 (22.5)
Source of admission, n (%)	Ward	0	488 (24.8)
Admission type, n (%)	Medical	0	1303 (66.2)
Admission type, n (%)	Surgical elective	0	76 (3.9)
Admission type, n (%)	Surgical urgency	0	588 (29.9)
Reason for admission, n (%)	Neurologic	0	363 (18.5)
Reason for admission, n (%)	Respiratory	0	519 (26.4)
Reason for admission, n (%)	Other	0	1085 (55.1)
CRRT n (%)	No	0	1642 (83.5)
CRRT n (%)	Yes	0	325 (16.5)

ICU = Intensive Care Unit, ER = Emergency Room, OH = Other Hospital, OR = Operating Room.

Table 2
Continuous characteristics of the population.

Variable	Missings	Values
n		1967
Ventilation days, median [Q1,Q3]	0	8.8 [3.6,19.8]
Age, median [Q1,Q3]	0	63.0 [51.0,71.0]
Real RR (rpm), median [Q1,Q3]	68 (3.5 %)	18.1 [16.8,20.7]
Set RR (rpm), median [Q1,Q3]	55 (2.8 %)	16.0 [15.0,18.1]
FiO2 (%), median [Q1,Q3]	9 (0.5 %)	35.0 [30.0,41.3]
FlowSet (L/min), median [Q1,Q3]	371 (18.86 %)	60.0 [53.0,62.0]
Set TV (L), median [Q1,Q3]	182 (9.3 %)	0.5 [0.5,0.5]
Real TV (L), median [Q1,Q3]	168 (8.5 %)	0.5 [0.5,0.6]
PEEP (cmH2O), median [Q1,Q3]	72 (3.7 %)	6.0 [5.0,8.0]
Peak Pressure (cmH2O), median [Q1,Q3]	85 (4.3 %)	23.9 [21.0,27.0]
Plateau Pressure (cmH2O), median [Q1, Q3]	272 (13.8 %)	19.1 [16.0,23.0]
SpO2 (%), median [Q1,Q3]	3 (0.2 %)	97.6 [96.6,98.7]
Driving Pressure (cmH2O), median [Q1, Q3]	283 (14.4 %)	12.6 [10.0,15.0]
Mechanical Power (J/min), median [Q1, Q3]	291 (14.8 %)	16.2 [13.3,19.7]
PaO2/FiO2, median [Q1,Q3]	96 (4.8 %)	244.0 [178.1,344.3]
SpO2/FiO2, median [Q1,Q3]	12 (0.6 %)	281.0 [235.1,330.0]
Weight (Kg), median [Q1,Q3]	0	75.0 [70.0,89.8]
Height (cm), median [Q1,Q3]	1 (0.1 %)	170.0 [165.0,175.0]
PBW (Kg), median [Q1,Q3]	1 (0.1 %)	66.0 [57.0,70.6]
Blood pH, median [Q1,Q3]	74 (3.8 %)	7.4 [7.4,7.4]
Blood PaCO2 (mmHg), median [Q1,Q3]	74 (3.8 %)	41.1 [37.6,45.1]
Blood HCO3(mmol/l), median [Q1,Q3]	562 (28.6 %)	26.7 [23.9,29.3]
RASS, median [Q1,Q3]	27 (1.4 %)	−3 [-2,-4]
APACHE II score, median [Q1,Q3]	45 (2.3 %)	16.0 [12.0,21.0]

RR = Respiration rate, TV = Tidal Volume, APACHE = Acute Physiology and Chronic Health Evaluation,

Different moments where the prediction of our model is superior to the baseline model value can be reviewed in Fig. 2.

To establish the MP cutoff point that will differentiate higher-risk situations, the relationship between MP and mortality was analyzed. Fig. 3 shows that we see an increase over 25 % mortality rate at 18 J/min of MP, defining the cutoff point.

When evaluating the results around the 18 J/min MP threshold, it is observed that the model is accurate 94.44 % of the time in predicting whether the MP will be higher or lower than 18 J/min, with an average sensitivity of 95.44 % and an average specificity of 93.94 %. The stability of the success rate regardless of whether the previous MP is above or below 18 can be appreciated in Fig. 4.A.

Furthermore, when evaluating only the MV moments in which a patient changes from < 18 J/min to $>= 18$ J/min or vice versa, a 16.94 % accuracy was obtained compared to 0 % of the baseline model. An average sensitivity of 19.33 % and an average specificity of 15.25 % were obtained. Our model is significantly better at predicting when a patient will change MP category. Fig. 4.B shows this more detailed evaluation.

4.4. Real-Time integration of the model

After developing the model and completing the real-time data pipeline integration on the web platform, clinicians have access to the real-time use of the model. In the web platform interface, a label has been added that displays the patient's current MP value as well as the

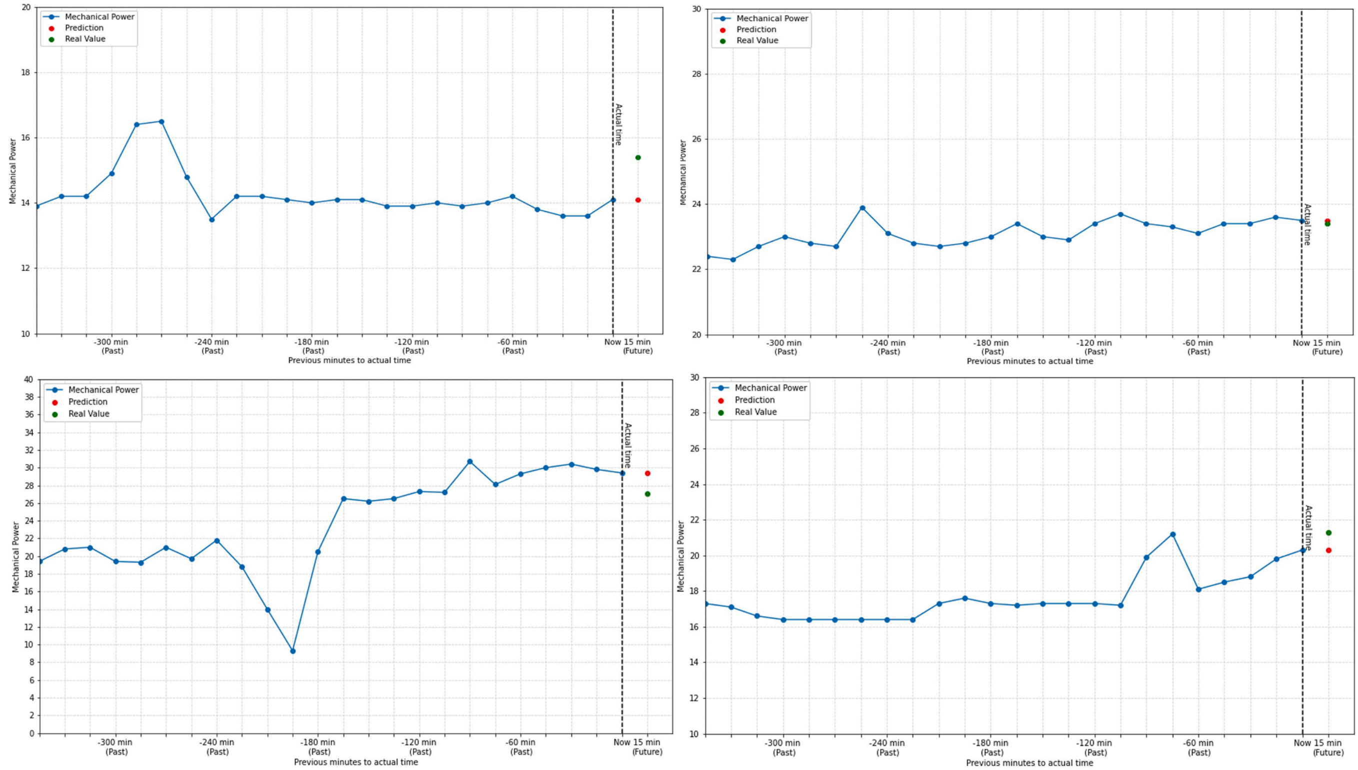

Fig. 1. Baseline predictive model. These plots represent the monitored Mechanical Power (MP) over time alongside the baseline prediction for MP's future values and the real future values. The blue line shows the observed MP up to the actual time of the prediction. Red dots are the predictions for the next 15 min interval. Green dots indicate the actual MP measurement recorded after predictions. Discrepancies between the predictions and the actual future MP values are indicators of the changes in the patients ventilation conditions that need adjustment.

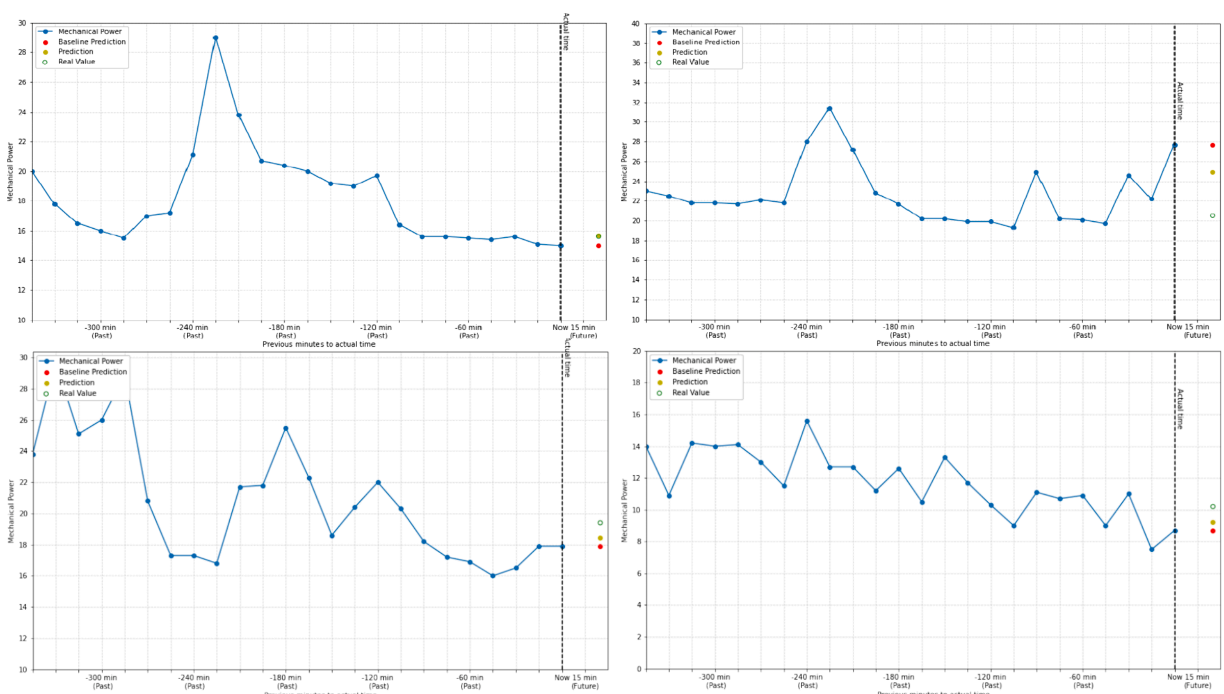

Fig. 2. Comparative between the predictions of our model against the baseline model. These plots illustrate the evolution of Mechanical Power (MP) in different patients and the forecasts of the baseline model and our Artificial Intelligence (AI) model. The blue line shows the observed MP up to the actual time of the prediction. Red dots are the MP predictions of the baseline model, yellow dots the MP predictions of our AI model and green circles are the real values in 15 min. This comparative visualization highlights the predictive performance of our model in relation to the baseline model.

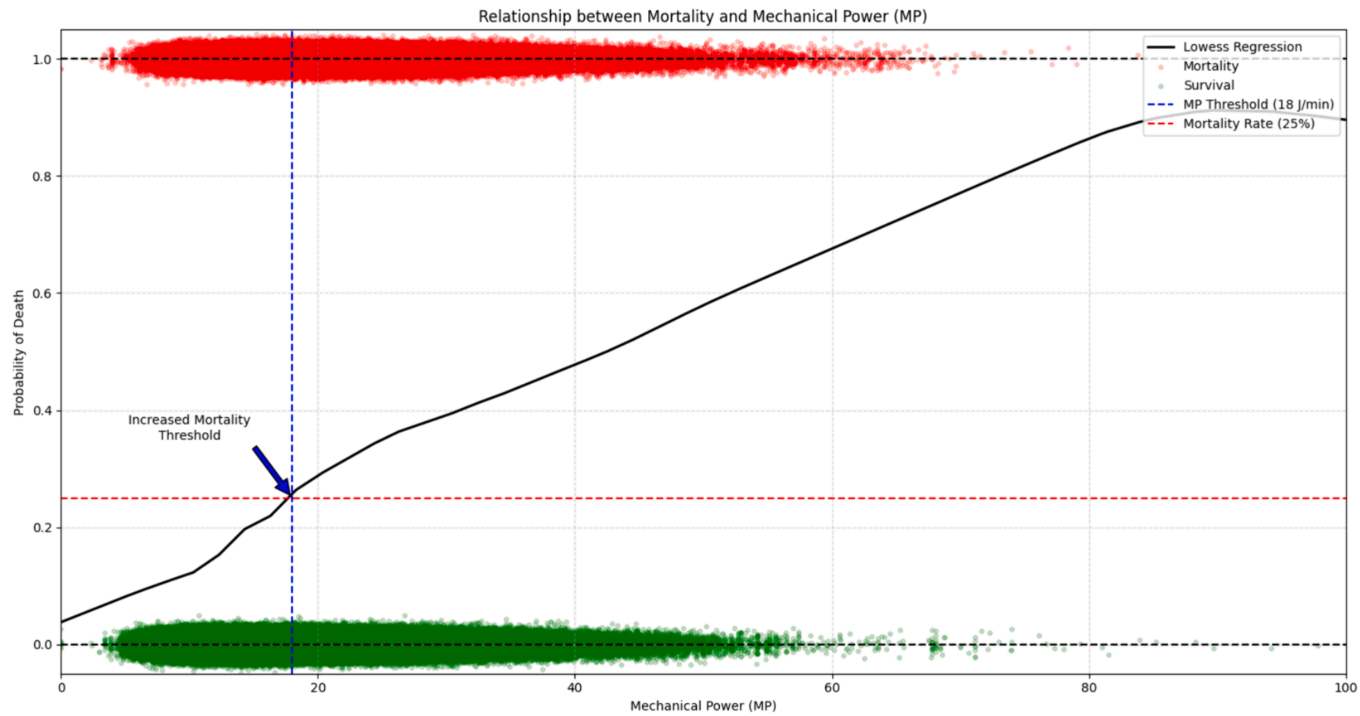

Fig. 3. Relationship between mortality and MP. This plot shows the relationship between mechanical power (MP) and mortality.Patients outcomes are marked as red (deceased) and green (survived) dots. The black line is the Lowess regression curve that represents the probability of mortality across different MP values. Blue and red lines cross each other at 18 J/min and 25 % probability of death, indicating the point at which a quarter of patients are deceased. This cross allows us to detect a critical cutoff point as it indicates the MP value from which the probability of mortality notably increases in MP.

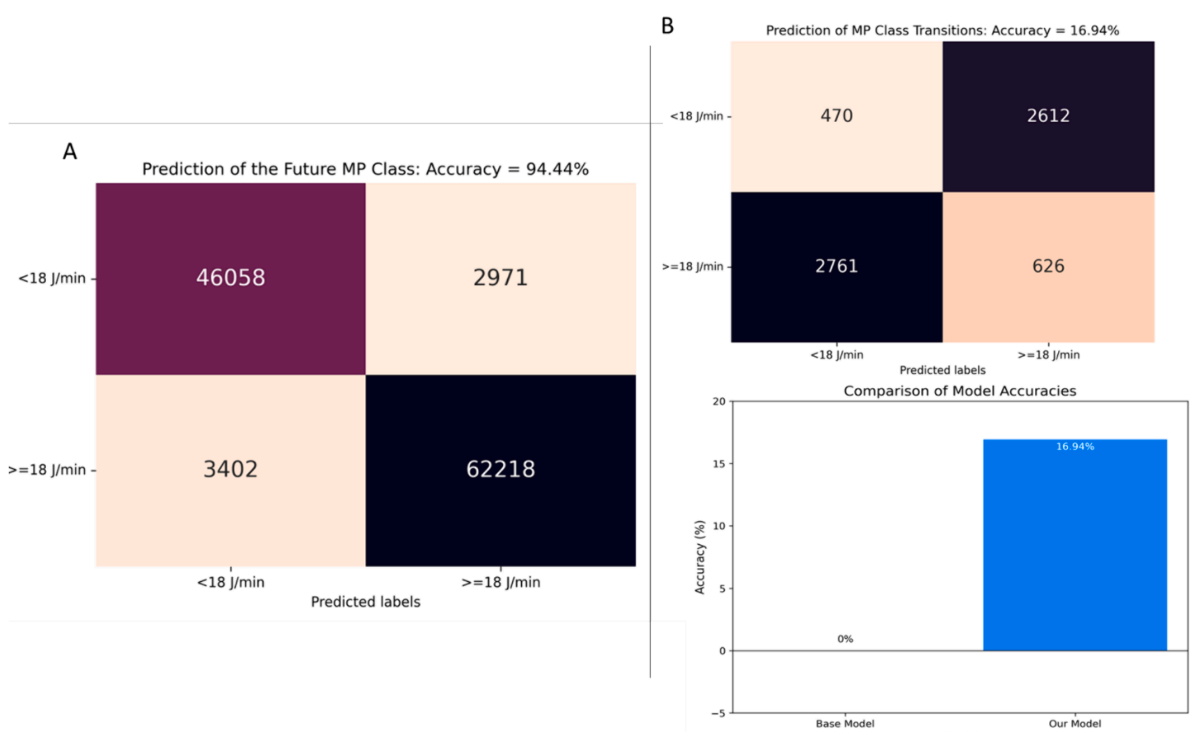

Fig. 4. Evaluation of the predictions around the 18 J/min threshold.This figure displays the evaluation of model predictions in relation to the 18 J/min MP threshold. Panel A shows a heatmap of the future MP class predictions, with an overall high accuracy of 94.44 %. Panel B illustrates the prediction of MP class transitions from one class to the other with an accuracy of 16.94 %, indicating the model’s ability to predict changes across the threshold. This ability is represented in the lower graph that compares the accuracies in MP class transitions of the base model and our model.

Fig. 5. Web platform developed. Visualization of the web platform interface developed for real-time monitoring and prediction of mechanical power (MP). Displayed are two patient monitoring boxes, BOX08 and BOX09, showing current tidal volume (VT), maximum VT, driving pressure (DP), current MP, and predicted MP. Alerts are indicated by red lights to signify when predicted values exceed threshold levels, and a 'CV' icon is present to indicate controlled ventilation status.

MP prediction for the next 15 min. It also indicates whether the MP is increasing or decreasing and uses colors to generate alarms when the MP exceeds the 18 J/min threshold. Fig. 5.

5. Discussion

The results obtained in this study represent a significant advancement in the application of AI in the management of IMV. Our deep learning model achieved a 20 % improvement in MSE (2.74) in predicting MP, demonstrated a 94 % accuracy in predicting whether MP would exceed the threshold of 18 J/min or not, and exhibited notable achievements in moments of critical changes in MP (16.94 % accuracy), a scenario where even minor improvements in prediction accuracy can have a significant impact on patient outcomes.

AI models have been widely used in the last 5 years with the aim of improving adherence to clinical practice guidelines in IMV [33] and predict clinical aspects related to the context of IMV [34]. To date, no model has been developed that predicts the future MP a patient will have. To establish some context the closest to our model was the one created by Hagan et al. in 2020, which predicted future Vt with a 10 % accuracy rate [35], or the model by Ghazal et al. that predicted SpO2 five minutes after making a change in the ventilator[36] this last one with an AUC between 0.54 and 0.72.

Besides our model's good prediction rate, the appeal of the model proposed in this work lies in its clinical applicability as it will allow the physician to have more personalized information when deciding whether to make changes in IMV parameters. Predicting MP in a 15-minute window with a 2.74 mean squared error is not just a theoretical achievement but represents a paradigm shift in patient care.

Regarding on how to apply our model to the clinical practice, the real impact of AI models based on large databases has been debated. Adequate implementation in clinical practice and rigorous prospective evaluation are needed[37]. We consider that the main difficulties in deploying our model in the real world are related to the dynamic nature of ICU environments. The ICU is characterized by rapid shifts in patient conditions, which, coupled with potential issues from computing devices, significantly complicates obtaining valid and reliable data. Computing errors, system downtimes, and data transmission failures can lead to incomplete or inaccurate data, which are critical challenges that must be addressed to ensure the effectiveness of real-time predictive modeling. In our study, we have applied the same data processing used for developing the model in our real-world implementation and have seen that it works with reliability.

Besides that, our group has focused on ensuring quality data in CIS for secondary use in clinical management and for the development of AI-based models [25]. This complete access to quality patient data, both recorded by professionals and coming from bedside devices and laboratory data, marks the difference between being able to deploy the model to real-world or not. Finally, we also propose a methodology that includes displaying the model's prediction to the clinician in an ergonomic way at the bedside and in real time. This methodology has already been published by our research group and has shown improved organization and distribution of resources in ICUs [38]. Even so, continuous evaluation and model recalibration, based on incoming real-world data, are essential steps to ensure sustained accuracy and reliability.

Our study has some limitations that should be highlighted. Firstly, in this study, we established a cutoff point of MP $>$ 18 J/min as it is the point at which more than 25 % of our population dies. This cutoff point correlates with the literature [19,23]. However, in recent years, there has been advocacy for a value of normalized MP by predicted ideal weight (PI) [20] or the size of the healthy aerated lung (baby lung concept) [39,40] which may lead to changing or individualizing this cutoff point in the coming years.

In second place, we did not differentiate between patients ventilated in volume control and pressure control modes, although in recent years a different MP formula has been proposed for patients with Pressure Control [41,42]. Perhaps if we had applied this formula to Pressure Control patients, the mean squared error would have improved.

As our last limitation, this model has been created and tested using data from a single Spanish ICU, making it currently not extrapolable to other populations. We believe that our model should not be thought as a ready-to.use product in other cohorts or locations. We think of our model as a technological process that can be adapted to other cohorts with mandatory adaptations like studying the available data, finding the similarities and differences between data, adapt the used variables to the new population of patients and a retrain of the model with new data that benefits from our previous training of the data. Future studies should be conducted to test this model in other populations and to learn from them, improving its metrics, and finding new potential limitations.

Despite the limitations mentioned, it is worth highlighting that this is an interdisciplinary work between clinicians experts in mechanical ventilation and data scientists. We have developed a predictive model to forecast MP and have implemented real-time visual alerts that provides doctors with valuable data-driven decision-making information, enabling early interventions in case of significant changes in MP. This advance represents a significant step towards optimizing the management of IMV and highlights the value of combining AI with clinical judgment in ICU patient care management. Until now, no one had created a predictive model of these characteristics.

These results are not only predictive but also open the door to new ways of monitoring and managing IMV in critically ill patients, enhancing data-driven medical care. Future studies will be necessary to test this model in other populations and its real utility in daily clinical practice.

6. Conclusions

The present study will assist clinicians in predicting an increase in MP and advancing in the necessary actions to prevent it. Prospective studies following its implementation in clinical practice through the proposed methodology will allow us to evaluate its true impact on the evolution of critically ill patients undergoing IMV.

CRediT authorship contribution statement

M. Ruiz-Botella: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **S. Manrique:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **J. Gomez:** Software, Formal analysis, Conceptualization. **M. Bodí:** Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Summary table.

What was already known on the topic:

- Invasive Mechanical Ventilation in ICUs can significantly increase the risk of developing Ventilator-Induced Lung Injury.
- Mechanical power has been identified as a critical parameter related to Ventilator-Induced Lung Injury and high values of mechanical power are associated with lung damage and mortality.

What this study added to our knowledge:

- It is possible to forecast mechanical power 15 minutes in advance with the use of Artificial Intelligence, improving a baseline model.
- Clinicians can use this model integrated into a web platform, enabling real-time predictions of mechanical power and adjustments to ventilation settings to mitigate VILI risk.

Appendix

Appendix A

The variables selected to be into the study for predicting MP were divided into 2 groups and selected by Pearson's correlation.

The first group includes the IMV variables, all of which showed a high correlation. The variables selected from this group used to calculate MP are: RR (correlation of 0.59), VT (correlation of 0.35), PEEP (correlation of 0.53), Ppeak (correlation of 0.71), Pplat (correlation of 0.52), DP (correlation of 0.29), and current MP (0.91).

The second group of variables defines the critical state of the patient. For IMV variables, those that did not show a high correlation with MP were included in this group. Those were set RR, FiO2, Flow set, Set VT, SpO2, PaCO2/FiO2. For the other type of variables, although these variables generally showed a low correlation, the selected ones had a correlation greater than 0.1 with MP. For categorical variables, each category was evaluated individually, selecting only those categories that exhibited a correlation higher than 0.1. These variables include height (cm), sex, weight (kg), PBW (Kg), RASS, arterial pH, PaCO2 (mmHg), HCO3 (mmol/l), Heart Rate (HR) (bpm), presence of continuous renal replacement therapy (CRRT), source of admission (emergency or operating room), reason for admission (neurological or respiratory), type of admission (medical or surgical), and admission type (urgent or elective).

Appendix B

The outlier detection and deletion of IMV variables were defined by clinical values stated by clinicians. Specifically, an extreme value was defined as a Respiratory Rate lower than 10, a VT lower than 200, a Peak Pressure lower than 15, a Plateau Pressure lower than 10, and a PEEP lower than 0.

Once the extreme values were eliminated, time intervals with missing data were completed. For IMV variables, missing data were filled with the previous value as long as this value had not been collected more than 4 h ago.

For variables defining the patient's critical state, simply the last value obtained before the prediction was used.

Appendix C

We derived new variables to get more information of the data to feed to the model. Two group of variables were derived. The first groups aim to capture whether the current value of a temporal variable is high or low in the context of the last few hours. We calculated these variables for each of the MV temporal variables, differences were calculated with respect to the maximum, minimum, average, and median of the last 6 h. From these derived variables, those with a correlation with MP greater than 0.1 were selected. The new variables derived where:

- MP-minMP, MP-medianMP, MP-meanMP, RR-maxRR, RR-maxRR, PEEP-minPEEP, PeakP-minPeakP, PeakP-medianPeakP, PeakP-meanPeakP, PlatP-minPlatP and DP-minDP.

The second group of derived variables aimed to quantify the interaction between each pair of MV variables. For each analysis window addition, subtraction, division, and multiplication between each pair was calculated. Those derived variables whose correlation with MP was greater than that of their individual components were selected. The new variables were:

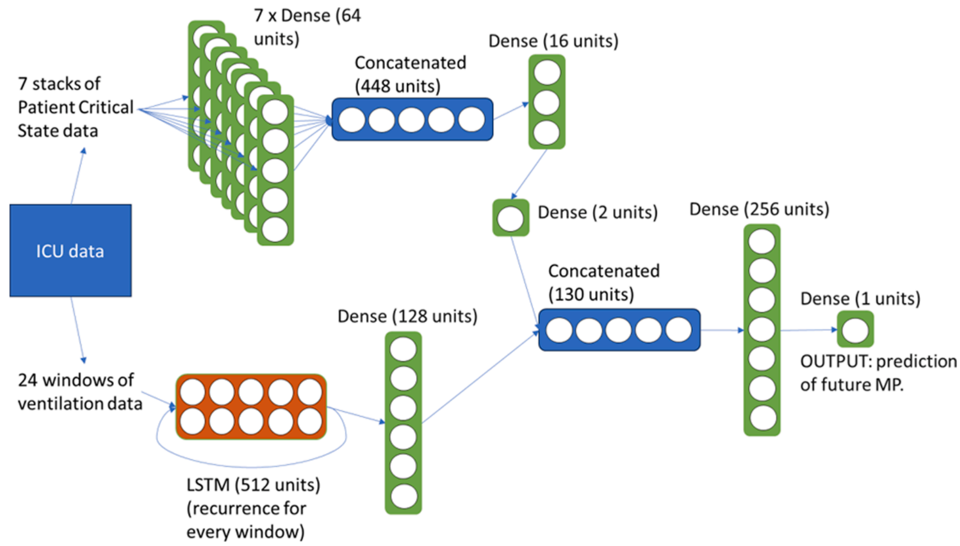
- RR + VT, RR/VT, RR + PEEP, RR/PEEP, RR + PeakP, RR/PeakP, RR + PlatP, RR/PlatP, VT/RR, VT + PEEP, VT/PEEP, VT + PeakP, VT/PeakP, VT + PlatP, VT/PlatP, PEEP/RR, PEEP/VT, PEEP + PeakP, PEEP + PlatP, PEEP/PlatP, PeakP/RR, PeakP/VT, PlatP/RR, PlatP/VT, PlatP/PEEP, PlatP-DP, DP/VT, DP/PEEP, DP-PlatP.

Appendix D

We trained our model to to minimize the mean squared error of the MP predictions. The architecture of the model it's shown in the Figure Appendix

D.

Figure Appendix D Representation of our proposed model for MP prediction.



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This figure illustrates the mixed neural network model used for real-time prediction of Mechanical Power (MP) from ICU data. At the top, the dense layers receive critical patient state variables at the time of prediction. At the bottom, the LSTM layers process temporal variables across 24 time windows. Both parts of the model are concatenated for final processing and generation of the MP prediction for the next 15 min. The number of units in each layer is indicated by the numbers in parentheses.

Regarding the training specifics of the model, we trained the model with a ranger optimizer, a combination of a Lookahead and a RectifiedAdam with a 0.0001 learning rate. A reduction in the learning rate is applied to avoid overfitting, we applied a reduce learning rate on plateau algorithm with a factor of 0.7, a patience of 12 epochs and a minimum learning rate of 1e-7. Also earlystopping was applied to avoid extra overfitting, monitoring the loss of the validation dataset and with a patience of 30 epochs. The model is trained twice consecutively to avoid falling into local minima of the mean squared error that could prevent improvement of the result.

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