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Knowledge Construction on NIV of COVID-19 for Managing the Patients by ML Techniques

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Abstract:

The COVID-19 non-invasive ventilation guidelines have been inconsistent across regions. The research team behind this review set out to answer questions about the usefulness of non-invasive ventilation in the early stages of a pandemic, as well as the quality and availability of relevant guidelines. The decision to begin Non Invasive Ventilation (NIV) in hypoxemic patients at risk for developing respiratory failure may be especially challenging in patients suffering from COVID-19. The potential for negative outcomes following delayed diagnosis of respiratory failure highlights the need for improved predictive models of NIV requirement. Care decision making based on information from covid 19's noninvasive ventilation and invasive mechanical ventilation is analysed using a Logistic Modeling Tree (LMT). In order to determine whether a patient would need NIV within the next 6, 12, 18, or 24 hours, it was trained on data from the MIMIC-III database. This work implemented a cohort of 524 COVID-19 patients from a single centre in Israel to validate the LMT algorithm. This work governs that an increase in prediction probability is accompanied by an increase in prediction accuracy. Efficiency at the MCCU is 74.81%, which is lower than that of competing systems by a wide margin. When compared to other models, the LMT's maximum output is 98.47% efficient. The MCCU's accuracy of 0.69 is lower than that of competing systems. When compared to alternative methods, the LMT's 0.98 accuracy stands as the industry standard for reliability. The recall for the MCCU is 0.75, which is lower than for any competing model. When compared to other models, the LMT's 0.98 recall is the highest. When compared to other systems, the kappa value of 0.56 shared by the MCCU and the DS is the lowest available. When compared to other models, the LMT's 0.97 kappa result is the highest. The 0.68 F-measure held by the MCCU is the lowest of any comparable system. When compared to other models like the 0.98 F-Measure, the results from the LMT are the best possible. When compared to other systems, the MCCU's 0.54 MCC capacity is among the lowest available. When compared to other models like the 0.97 MCC, the LMT has the best results by far. When compared to other systems, the MCCU's ROC of 0.76 is the lowest. When compared to competing models, the LMT's 0.99 ROC is the highest. With 0.65 PRC, the MCCU has the fewest reserves of any major system. In comparison to other models, such as the 0.99 PRC, the LMT yields the best results. The LMT model performed well compare with other models due to its performance. The general ICU population and COVID-19 patients were successfully predicted to require noninvasive ventilation 6, 12, 18, or 24 hours in advance using this model. Despite the low overall precision, using the prediction probability as an indicator of the accuracy has the potential to help with decision making in patients with hypoxemic respiratory failure. The LMT model explores best outcome with low deviation compare with other models.

Keywords: COVID19,NIV, ICU, LMT,

I Introduction

High rates of morbidity and mortality accompany acute hypoxemic respiratory failure. It is a complex condition that can arise from a variety of different factors and may ultimately result in impaired lung function and respiratory muscle pump failure.[1] Both invasive mechanical ventilation (IMV) through tracheal intubation and noninvasive respiratory support (NIR) using high flow systems are options for providing respiratory care.[2] Long-term high-flow oxygen therapy or NIV use after respiratory failure has been misdiagnosed may increase mortality. As the choice of whether or not to begin IMV is not always black and white, it is crucial to create decision-support tools that can identify those patients who are likely to fail while receiving only noninvasive treatment.[3] The treatment of COVID-19 patients with respiratory failure, in whom approximately 15% of the population uses NIV and high flow oxygen therapy [4], makes these decisions more important than ever.

To better predict hypoxemic respiratory failure, we developed a new model using the existing, large dataset from the Medical Information Mart for Intensive Care (MIMIC-III).[5] Models trained on a population before the spread of COVID-19 may not accurately predict the respiratory failure that results from the virus.

Because of the limited size of the training cohort, it is not sufficient to train models on data from the COVID-19 population collected at a single hospital.[6] In light of this, we opted for a two-pronged approach, first training a machine learning (ML) predictive model on a massive dataset of the general population pre-COVID-19, and then adjusting this model for the smaller COVID-19 cohort.[7]

Although mortality rates and associated morbidity remain high, the field of respiratory care for acute respiratory failure has made great strides in recent decades. Good results can be achieved when the increased respiratory load is compensated for using noninvasive methods.[8] A recent meta-analysis compared NIV with standard oxygen therapy and found that patients who used NIV with face masks or helmets had a lower risk of death.[169 lower risk of death and are less likely to require intubation.[17] Delayed IMV initiation may have unintended consequences, including but not limited to the aforementioned increase in mortality.[10] While the dangers of ventilators have been known for quite some time, there has been a growing body of research on the risks of lung injury from inhaling smoke or other particles in recent years. [11]If a patient has a high risk of lung damage because of something like a high respiratory drive, letting them stay on noninvasive support may lead to worse outcomes in the long run compared to starting IMV sooner.[12] Patients with COVID-19 who require IMV have a much higher risk of death than those with general acute hypoxemic respiratory failure or even other viral pathogens, ranging from 35% to 97%[13].

Possible methods have been developed to identify those who are likely to fail with noninvasive support and in whom IMV could benefit from being started at an earlier stage. Very few models have created a scale (HACOR) that takes into account a patient's heart rate, acidosis, consciousness, oxygenation, and respiratory rate to foretell NIV failure.[14] In certain subgroups, this method achieved a diagnostic accuracy for NIV failure higher than 80%. Hospital mortality rates were found to be lower when this tool was used, and its efficacy was later independently verified. Univariate analysis in a previous study with NIV after extubation[15] found that certain parameters were linked to reintubation. Multivariate analysis, however, revealed that pneumonia was the only independent predictor of NIV-assisted extubation failure in the critically ill.

Prediction of respiratory deterioration and failure is a growing area of application for artificial intelligence and machine learning algorithms. Two machine learning methods, logistic regression and XGBoost, were developed and studied by Zeidberg et al.[16] in the context of patients with acute respiratory distress syndrome. Patients with a four-fold increased risk of deterioration were most accurately identified using L2 logistic regression, which achieved an area under the ROC curve of 0.81. The COVID-19 population has been the focus of several research initiatives. By combining machine learning tools, primarily ensemble decision trees, with the knowledge of physicians, Ferrari et al.[7] were able to predict 48 hours in advance, with an accuracy of 84%, which patients would go on to develop moderately-severe respiratory failure. With the help of XGBoost for fitting decision trees, Burdick et al. were able to achieve an AUC of 0.866 in the READY trial[18] by identifying patients who would deteriorate within 24 hours and require IMV. To better predict which COVID-19 patients would deteriorate after 48 h, a recent study[19] used an XGBoost-based model, which achieved an AUC of 0.77 and significantly outperformed a previously established early warning score. This research article organizes in section 2 presents related definition and proposed methodology, section 3 focuses on outcome and analysis section shows conclusion of the research work.

II Terms and Methods

This section governs that the dataset collection, terms and proposed methodology for getting an efficient results.

Dataset Collections:

The dataset collected from MIMIC-III Clinical Database Demo [20]. The variables were continuously measured and stored in the electronic health record. While some of the variables were static, such as age or sex, most variables were dynamic, with periodic measurements from monitoring systems and labs. The relevant parts of the database were reformatted to the HDF5 file format, deemed more suitable for ML processing.

Table 1: Meta Data

S.No	Name of the attribute
1	Age
2	alanine aminotransferase
3	Albumin
4	alkaline phosphate
5	anion gap
6	arterial base excess
7	asparate aminotransferase
8	Basophils
9	Bicarbonate
10	Calcium
11	calcium ionized
12	Chloride
13	chloride urine
14	Cholesterol
15	Cpk
16	Creatinine
17	creatinine urine
18	Crp
19	d-dimer
20	diastolic blood pressure
21	Eosinophils
22	Ferritin
23	Fibrinogen
24	glascow coma scale total
25	Glucose
26	heart rate
27	Hematocrit
28	Hemoglobin
29	Lactate
30	lactate dehydrogenase
31	Lymphocytes
32	lymphocytes atypical
33	Magnesium
34	mean blood pressure
35	mean corpuscular hemoglobin
36	mean corpuscular hemoglobin concentration
37	mean_blood_pressure
38	neutrophils
39	oxygen saturation
40	partial pressure of carbon dioxide
41	partial pressure of oxygen
42	partial thromboplastin time

43	ph
44	ph urine
45	phosphorous
46	platelets
47	potassium
48	prothrombin time inr
49	prothrombin time pt
50	red blood cell count
51	respiratory rate
52	ROX
53	sodium
54	systolic blood pressure
55	temperature
56	total protein
57	total protein urine
58	troponin-t
59	weight
60	white blood cell count

Methods

Locally weighted learning (LWL): That's a Lazzy model, by the way. Assigns weights to instances based on an instance-based algorithm, which are then used by the Weighted Instances Handler that you designate.

Multi Class Classifier Updateable (MCCU): A meta-classifier that can be used with 2-class classifiers to manage multi-class datasets. This classifier can also use error-correcting output codes to further improve precision. The initial classifier used must be one that can be improved upon.

Decision Stump (DS): Training in the construction and application of a deciding stump. In most cases, this is employed in tandem with a "boosting" algorithm. Does Mean-Square Error-Based Regression or Classification (or Both) (based on entropy). As a separate value, missing data is accounted for.

Logistic Model Trees (LMT): 'Logistic model trees' are a type of classification tree in which the leaf nodes each represent a logistic regression function. The algorithm can handle missing values, numeric attributes, nominal attributes, and binary and multi-class target variables.

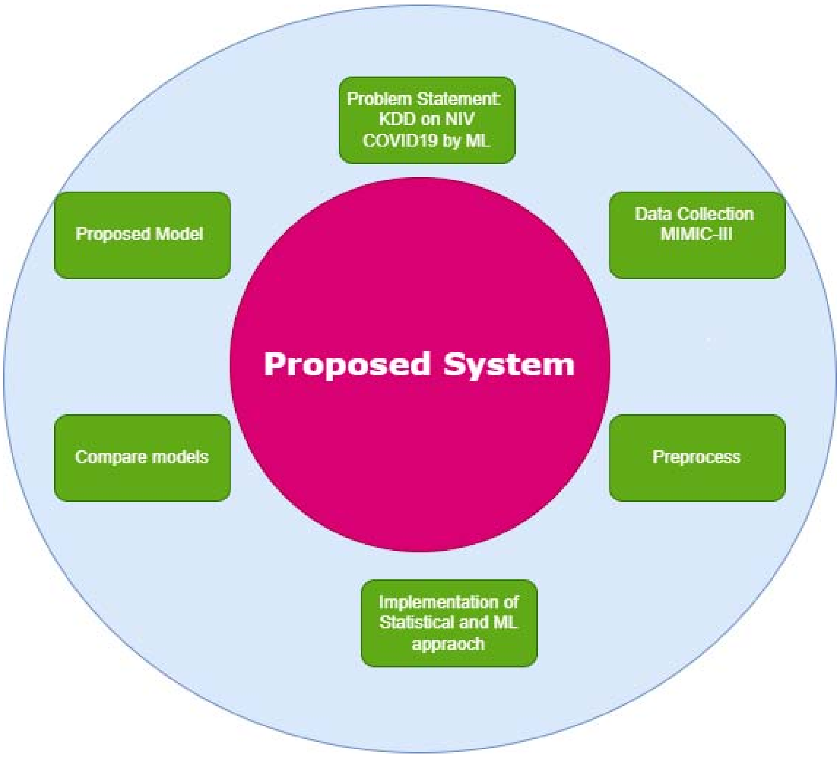

Figure 1: Proposed method

The above algorithms are implemented in 10 % of testing and 90% of training in weka 3.9.5 open source data mining tool for getting an efficient results.

III Outcome and Interpretation

This work focuses on results and discussions of NIV for covid 19 patient management. The table shows that the time, accuracy, precision and recall performance of LWL,MCCU,DS and LMT learning models.

Table 2: Time and Efficient Performance of selected leering models

S.No	Learning Model	Time	Accuracy	Precision	Recall
1	LWL	0	79.01%	0.85	0.79
2	MCCU	2.47	74.81%	0.69	0.75
3	DS	0.02	75.19%	0.83	0.75
4	LMT	4.25	98.47%	0.98	0.98

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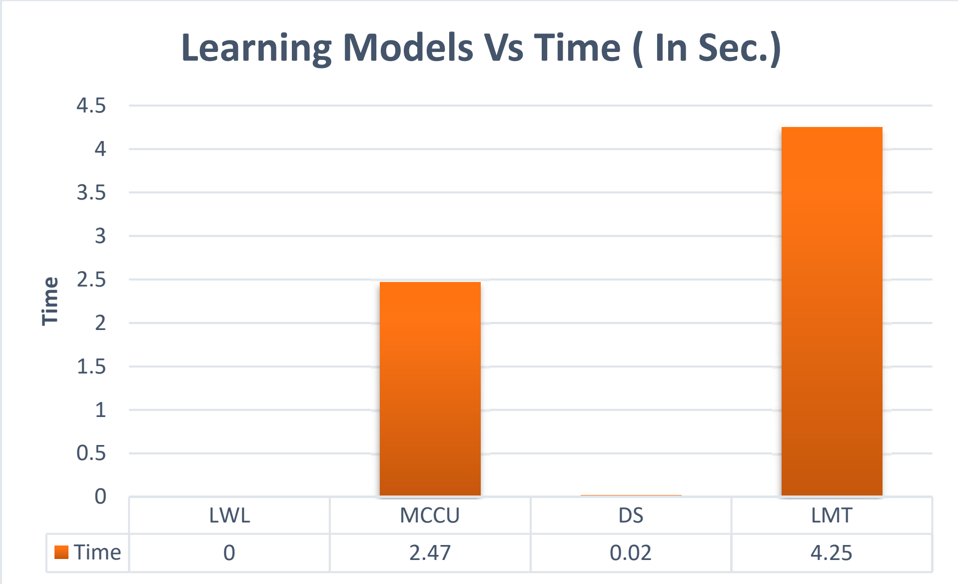

Figure 2: Performance of Time (In Seconds) Vs Learning Models

The above diagram 2 shows that the time distribution for making model of various learning systems. The LWL sucks zeros seconds for making its system. The LMT sucks 4.25 seconds for making its model which is maximum level of other selected models. The DS sucks 0.02 seconds and the MCCU sucks 2.47 seconds for making their models.

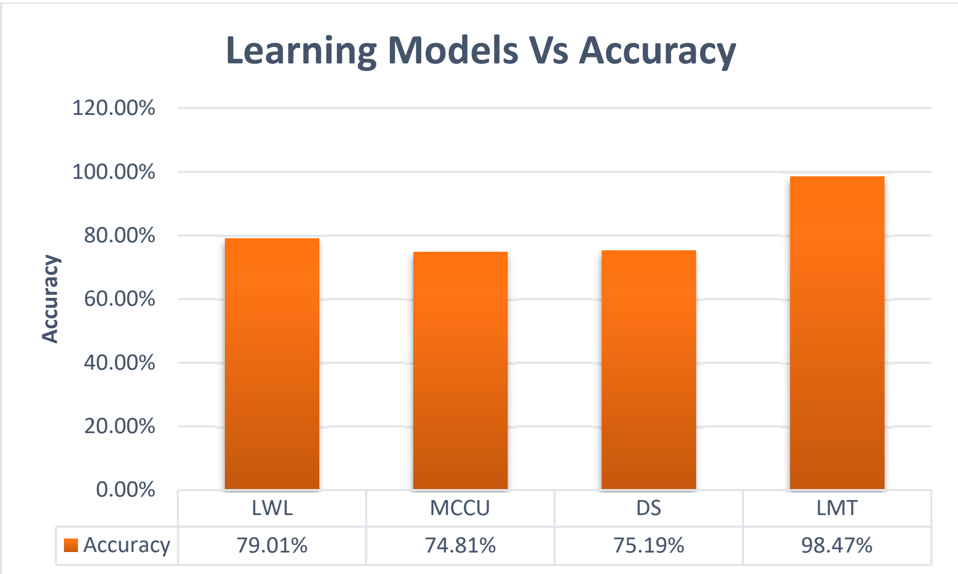

Figure 3: Performance of Accuracy Vs Learning Models

The above diagram 3 shows that the accuracy distribution of selected learning systems. The MCCU holds 74.81% efficiency which is least with other systems. The LMT holds maximum outcome compare with other models such as 98.47% efficiency. The LWL holds 79.01% accuracy and DS holds 75.19% accuracy.

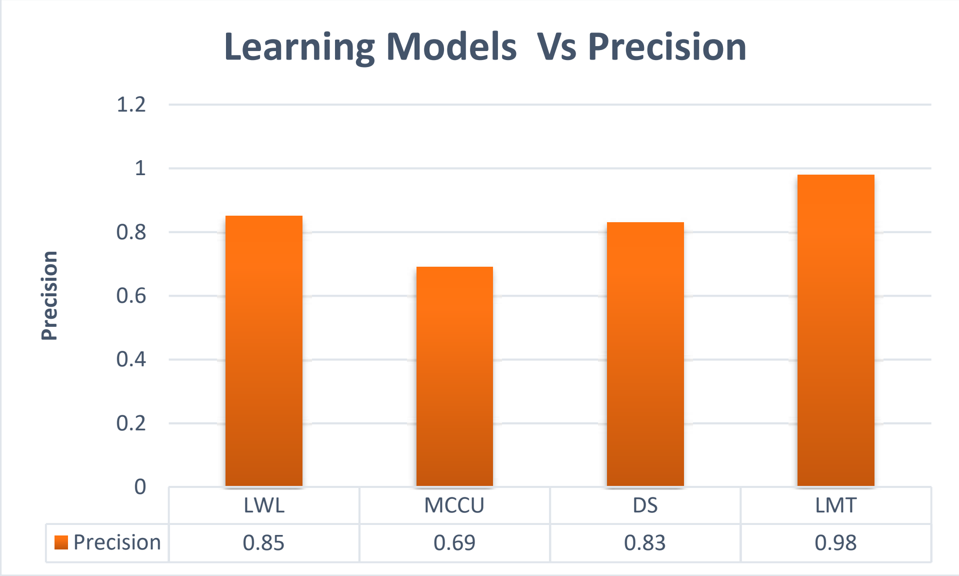

Figure 4: Performance of Precision Vs Learning Models

The above diagram 4 shows that the precision distribution of selected learning systems. The MCCU holds 0.69 precision which is least with other systems. The LMT holds maximum outcome compare with other systems such as 0.98 precision. The LWL holds 0.85 precision and DS holds 0.83 precision.

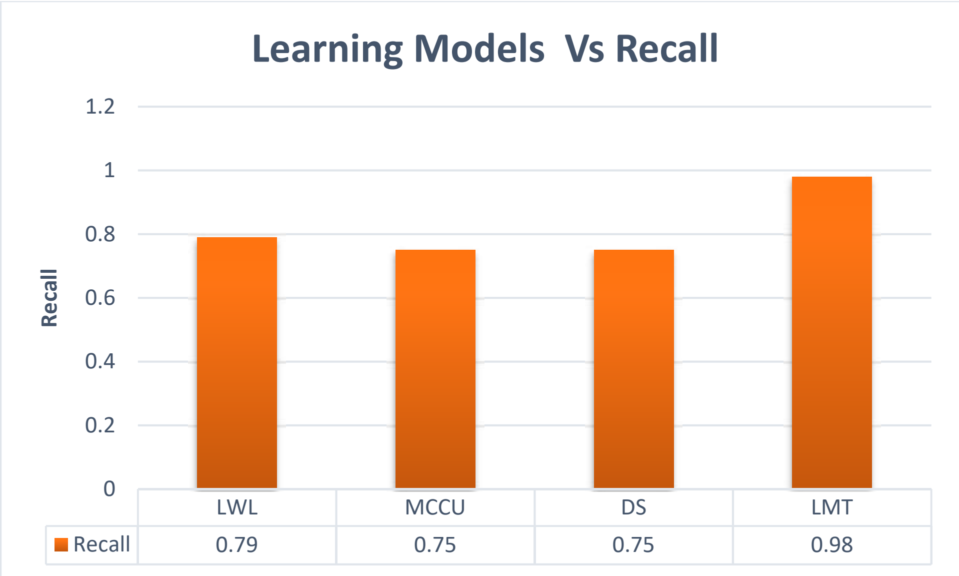

Figure 5: Performance of Recall Vs Learning Models

The above diagram 5 shows that the recall distribution of selected learning systems. The MCCU holds 0.75 recall which is least one compare with other models. The LMT holds maximum outcome compare with other models such as 0.98 recall. The LWL holds 0.79 recall and DS holds 0.75 recall.

Table 3: Statistical performance of selected leering models

S.No	Learning Model	Kappa	F-Measure	MCC
1	LWL	0.62	0.73	0.65
2	MCCU	0.56	0.68	0.54
3	DS	0.56	0.69	0.59
4	LMT	0.97	0.98	0.97

The above table 3 shows that the kappa statistic,F-measure and Matthews Correlation Coefficient values of LWL,MCCU,DS and LMT learning models.

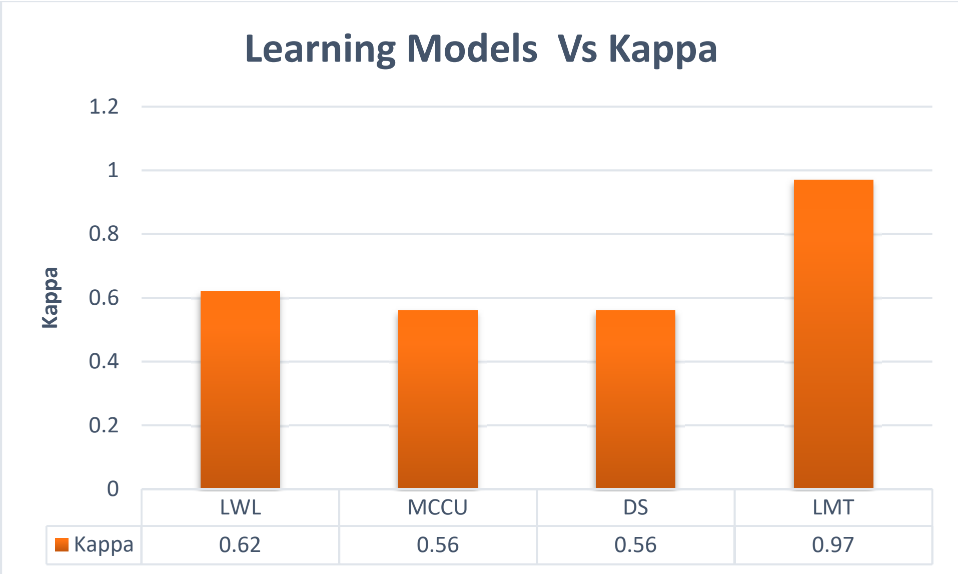

Figure 6: Performance of Kappa Vs Learning Models

The above diagram 6 shows that the kappa distribution of selected learning systems. The MCCU and DS holds same outcome, 0.56 kappa which is least one compare with other systems. The LMT holds maximum outcome compare with other models such as 0.97 kappa. The LWL holds 0.62 kappa.

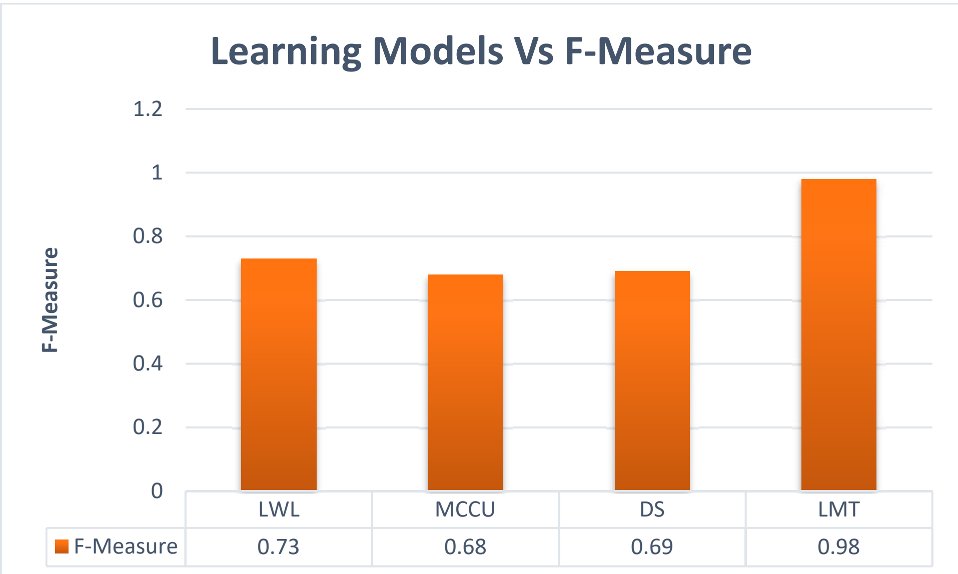

Figure 7: Performance of F-Measure Vs Learning Models

The above diagram 7 shows that the F-Measure distribution of selected learning systems. The MCCU holds 0.68 F-Measure which is least one compare with other systems. The LMT holds maximum outcome compare with other models such as 0.98 F-Measure. The LWL and DS holds 0.73 F-Measure, 0.69 F-Measure respectively.

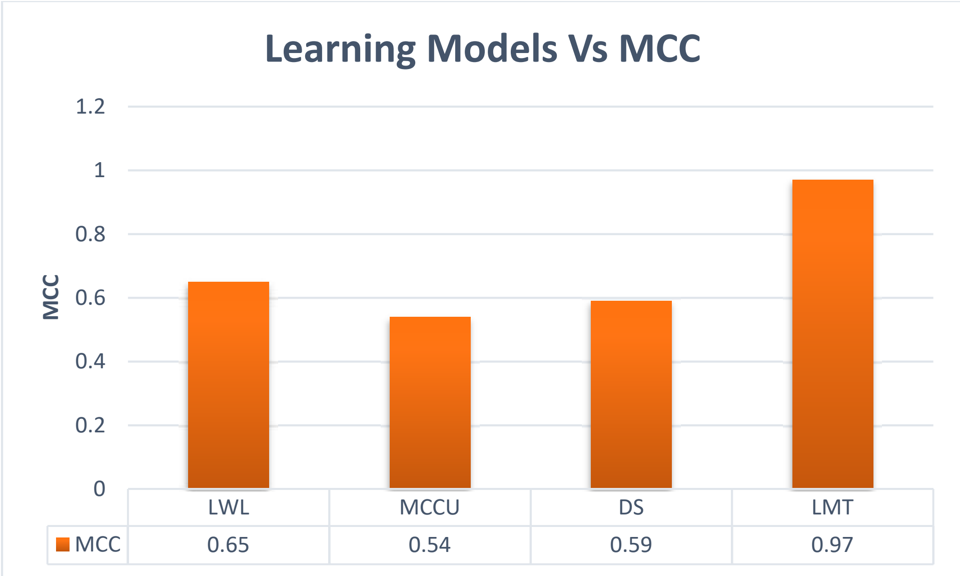

Figure 8: Performance of MCC Vs Learning Models

The above diagram 8 shows that the MCC distribution of selected learning systems. The MCCU holds 0.54 MCC which is least one compare with other systems. The LMT holds maximum outcome compare with other models such as 0.97 MCC. The LWL and DS holds 0.65 MCC, 0.59 MCC respectively.

Table 4: ROC and PRC performance of selected leering models

S.No	Learning Model	ROC	PRC
1	LWL	0.97	0.94
2	MCCU	0.76	0.65
3	DS	0.8	0.7
4	LMT	0.99	0.99

The above table 4 shows that the Receiver Operating Characteristic curve and Precision Recall Curve performances of LWL, MCCU, DS and LMT learning models.

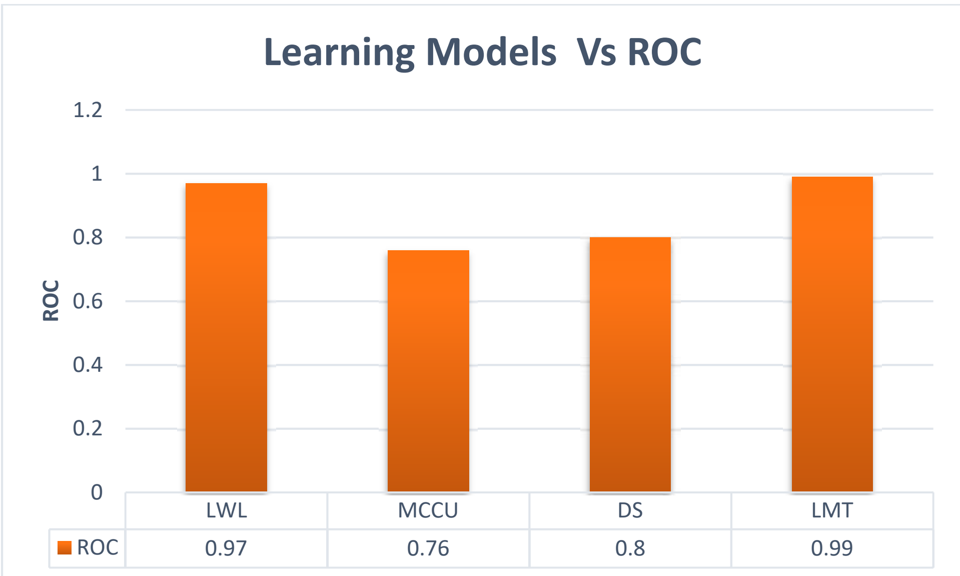

Figure 9: Performance of ROC Vs Learning Models

The above diagram 9 shows that the ROC distribution of selected learning systems. The MCCU holds 0.76 ROC which is least one compare with other systems. The LMT holds maximum outcome compare with other models such as 0.99 ROC. The LWL and DS holds 0.97 ROC and 0.80 ROC respectively.

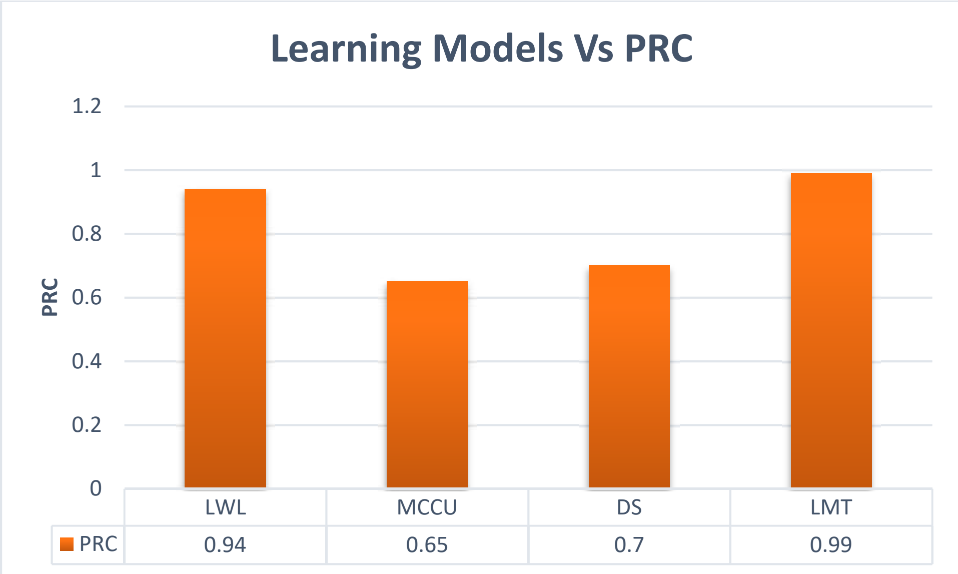

Figure 10: Performance of PRC Vs Learning Models

The above diagram 10 shows that the PRC distribution of selected learning systems. The MCCU holds 0.65 PRC which is least one compare with other systems. The LMT holds maximum outcome compare with other models such as 0.99 PRC. The LWL and DS holds 0.94 PRC and 0.70 PRC respectively.

Table 5: Deviation distributions of selected leering models

S.No	Learning Model	MAE	RMSE	RAE	RRSE
1	LWL	0.17	0.3	42.05%	65.97%
2	MCCU	0.17	0.41	40.46%	89.31%
3	DS	0.22	0.34	53.28%	73.90%
4	LMT	0.02	0.1	4.28%	22.54%

The above table 5 shows that the mean absolute error,root mean squared error,relative absolute error, and root relative absolute error performances of LWL, MCCU, DS and LMT learning models.

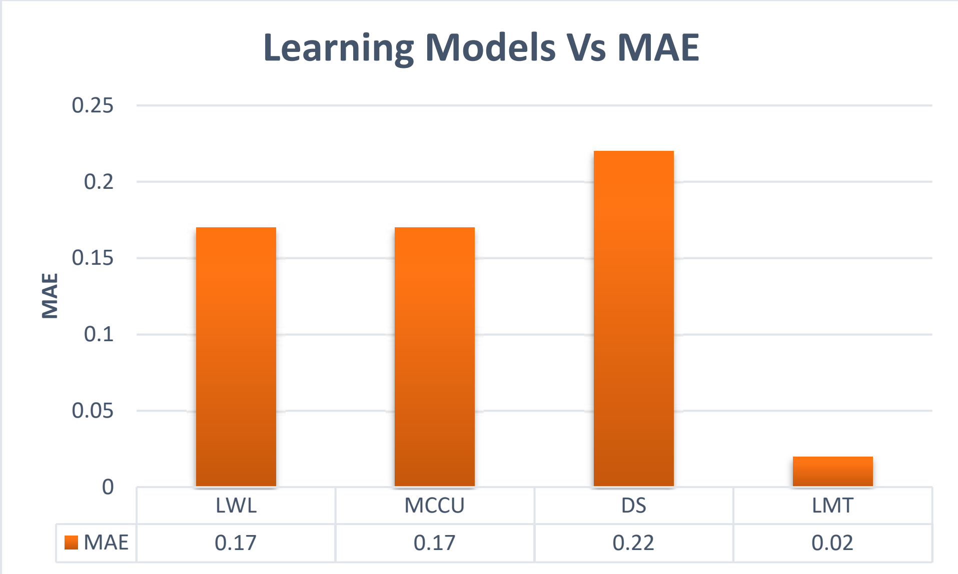

Figure 11: Performance of MAE Vs Learning Models

The above diagram 11 shows that the MAE distribution of selected learning systems. The MCCU and LWL holds 0.17 MAE which is least performance compare with other models. The LMT holds 0.02 MAE which is performing well. The DS holds 0.22 MAE.

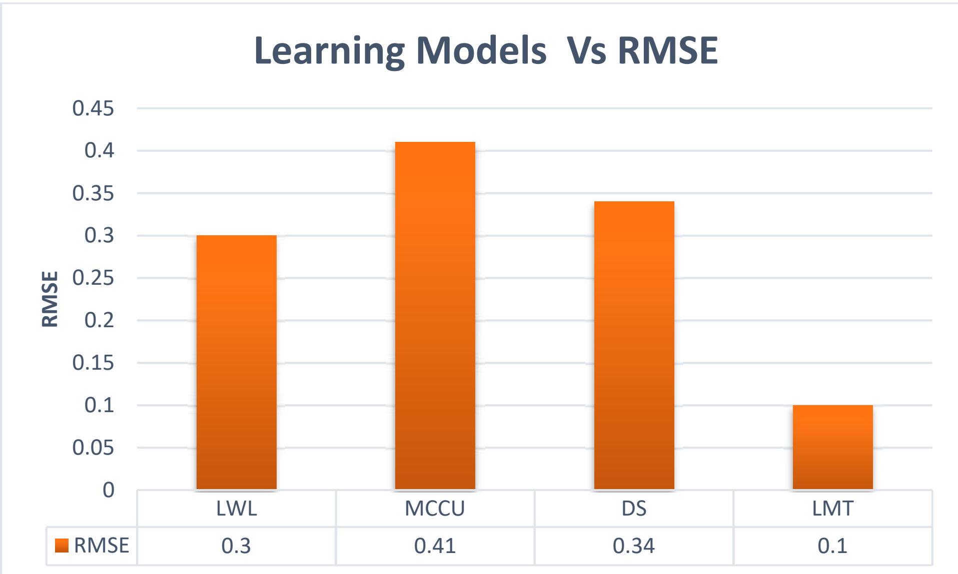

Figure 12: Performance of RMSE Vs Learning Models

The above diagram 12 shows that the RMSE distribution of selected learning systems. The MCCU holds 0.41 RMSE which is least performance compare with other models. The LMT holds 0.1 RMSE which is performing well. The LWL holds 0.30 RMSE and DS holds 0.34 MAE.

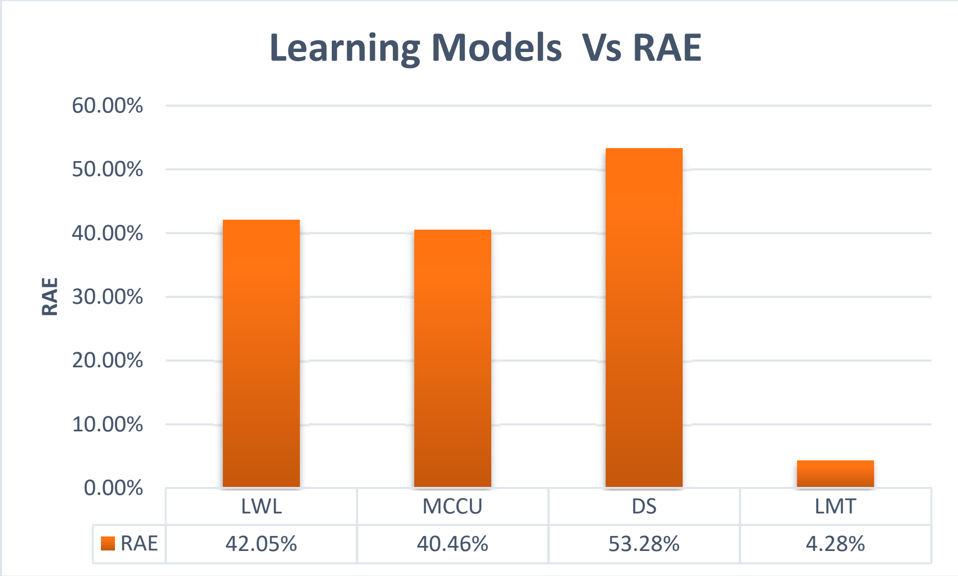

Figure 13: Performance of RAE Vs Learning Models

The above diagram 13 shows that the RAE distribution of selected learning systems. The LWL holds 42.05% RAE which is least performance compare with other models. The LMT holds 4.28% RMSE which is performing well. The MCCU holds 40.46% RAE and DS holds 53.28% RAE.

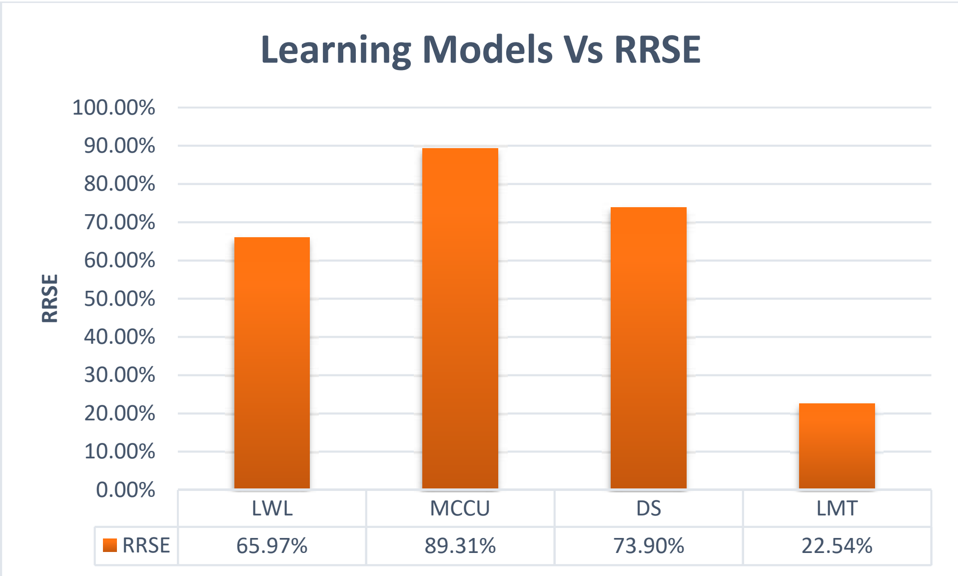

Figure 14: Performance of RRSE Vs Learning Models

The above diagram 14 shows that the RRSE distribution of selected learning systems. The MCCU holds 89.31% RRSE which is least performance compare with other models. The LMT holds 22.54% RMSE which is performing well. The LWL holds 65.97% RRSE and DS holds 73.90% RRSE.

IV Conclusion

Our adapted and trained prediction model showed good predictive abilities for up to 24 hours before the start of noninvasive ventilation, which may help in making that decision. The model's accuracy has been proven on a large patient cohort during training and testing, suggesting that it may be better than previously described models. The model's prediction should be understood in terms of probabilities rather than as a simple yes/no question, and low overall precision could still potentially limit clinical application. In order to evaluate and enhance its efficacy across settings and patient populations, it requires independent validation from other teams. This system recommends that the Logistic Modelling Tree (LMT) based on this performance.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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