A Convolutional Neural Network Model for Prediction of ICU Performance Metrics: Time Series and Image Transformation Approaches

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Abstract: In our study we used Convolutional Neural Network (CNN) to predict Intensive Care Unit (ICU) performances of patients via images generated from patients' Sequential Organ Failure Assessment (SOFA) scores which are used to assess the acute morbidity of intensive care unit patients. In our study we propose a novel method to predict ICU performances; mortality during the stay in ICU, mortality in one year after discharge from ICU, readmission and length of stay of ICU patients. We trained CNN models with images generated from multivariate time series data. Our model development process consists of two steps; converting SOFA scores of patients into an image and training the CNN with generated images to predict patients' ICU performances. We search for the best performing image generation algorithm which has the highest AUROC value for each prediction. Our model gives us AUROC values for mortality in ICU, readmission after discharge from ICU and length of stay of patients in ICU as 0.83, 0.84, 0.87, 0.56 respectively. We compare our methods' performance with random forest, support vector machine, Logistic regression and ensemble of these algorithms. The proposed image-based method in which we use the first day SOFA scores outperform the random forest, support vector machine and logistic regression algorithms. Our method performed similar to the studies in literature in terms of predicting mortality in ICU using first day data with an AUROC value of 0.83. Our model's performance would be improved with further feature engineering.

1 INTRODUCTION

Throughout all stages of the COVID-19 pandemic, ministries of health, hospital administrations and medical institutions noticed the importance of management of Intensive Care Units (ICU). Both administrative and medical departments of medical institutions are in search of an insight about patients' length of stay, mortality rates and readmission rates after they are discharged from the ICU. Management of medical facilities and medical resources appears as the key factors for fighting the COVID-19 pandemic. Even though importance of efficient utilization of intensive care units became apparent during the COVID-19 pandemic, there have already been studies carried out since 1970s on predicting mortality rates via medical records. Hospital managers need reliable information for planning utilization of facilities and resources. As Roehrig et al. (Roehrig, 2015) stated that time of discharge as early as possible from ICU may play an important role for developing strategies of resource consumption optimization; however, unplanned readmission of hospitalized patients to an ICU can cause unwanted outcomes. Patients who are discharged from the ICU may need to be readmitted to the ICU after a short period of time. The high number of unplanned readmissions leads to unnecessary expenses in healthcare, lowers the patients' quality of life, and increases the risk of hospital-acquired infections and/or complications (Goldfrad, 2000).

In addition to managerial and administrative needs of hospitals, medical doctors need to know the severity of the patients' cases to make decisions on treatment methods and inform both patients and their relatives about the possible outcomes of the treatment

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process. Therefore, monitoring the wellbeing of intensive care unit patients and/or severity of the cases of the patients are used as a predictor for ICU performances of patients in concern (Woldhek, 2017). These studies also provided us feedback about the performance of measurements on predicting the conditions of the patients.

Predicting the length of stay, mortality, and readmission is critical in efficiently managing the ICUs (Garrison, 2017). Studies discussed the necessity of utilizing different variables and more sophisticated machine learning techniques to improve the models' prediction performance (Low, 2015). In this study we investigate the CNN model which uses the recorded time series of an ICU patient as input. We convert the time series data to images and train the CNN model with these images. Recorded data can be classified under three segments; universal categorical segmentation features such as age, gender etc., domain based categorical segmentation features such as ICU type, comorbidity etc., and domain-based measurements such as clinical and laboratory data recorded in certain time intervals. Domain-based measurements are the data collected during the stay in ICU.

Domain-based measured features can also be used to create scoring systems such as Acute Physiology and Chronic Health Disease Classification System II (APACHE II), Simplified Acute Physiology Score 3 (SAPS 3) and Sepsis Sequential Organ Failure Assessment (SOFA). These scoring systems are built from clinical and laboratory measurements aimed to be used for building prognostic models for in hospital mortality (Moreno, 2006).

SOFA scores which would take a value between one and four, are used as measures for severity of the case of a patient in six categories; cardio, nervous, renal, liver, coagulation, and respiratory (Vincent, 1996). Such scoring systems produced from clinical measurements are used as predictors for the length of stay and mortality rate after discharge. After 1990s SOFA score gained importance for scoring severity of cases of ICU patients (Seymour, 2016). We produce SOFA scores from clinical values measured for each patient by medical personnel. There is a reference chart to calculate SOFA scores (Singer, 2016).

In our study we use SOFA scores of the patients as principal features to create prognostic machine learning models built to predict length of stay in ICU, mortality rates during and after discharge and predicting whether an ICU patient is going to be readmitted or not in one year after discharge. In addition to machine learning models, our distinct focus is on employing 2D Convolutional Neural Networks (CNN) to predict ICU performances of patients. First, we generate images to train the CNN using first day SOFA scores and investigate the best performing image generation algorithm. After finding out the best performing image generation algorithm we evaluate various epoch and batch size combinations to improve the performance of the CNN. We predicted mortality in ICU with an AUROC value of 0.83 which is better than the findings of the Brito et al. They predicted the mortality in ICU with an AUROC value of 0.82 via using admission SOFA scores (Brito, 2017).

2 LITERATURE REVIEW

There are various studies in Literature to predict the mortality in ICU, readmission to ICU within one year after discharge from ICU, and length of stay in ICU. Holder et al. concluded the importance of SOFA scores of the first 5 days for predicting in hospital mortality rate in a study done on a dataset of 1290 patients. However, additional SOFA scores do not improve the performance of the integrated discriminatory index (IDI) model. They have used the worst SOFA scores which means that the maximum SOFA score is used as input for multi variate analysis (Holder, 2017).

In 2017 de Brito et al conducted a study and arrived at the following results: SOFA's predictive power for binary classification of mortality in the ICU was good in all time points. Area Under the Receiver Operator Characteristics curves (AUROC) were 0.82 (95% CI (Confidence interval): 0.795 to 0.844) for admission SOFA, 0.827 (95% CI: 0.795 to 0.856) for third day SOFA and 0.827 (95% CI: 0.779 to 0.869) for fifth day SOFA (Brito, 2017).

In 2017 Gupta et al carried out a study on 84 elderly patients who were admitted to a medical ICU. They have used a statistical analysis with initial SOFA values and SOFA values after admission to ICU and concluded that there is a positive correlation between SOFA values and mortality rates. They have used logistic regression and their results are as follows: for every 2 points of increase in SOFA values the mortality rate increases 10% (Gupta, 2017). However, this study is limited to a very tiny population of ICU patients (Medical ICU and age is larger than 60).

Aperstein et al. have used 36 machine learning models and the best performing model is achieved by an ensemble of linear and logistic regression. They have used SOFA scores and increased the robustness of the models by using? gastointestinal data. Most of the models' performances are measured with AUC values varying between 0.8645 and 0.9146 (Aperstein, 2019).

Meyer et al. have used 44 features to predict mortality within 90 days after discharge. They have developed an RNN model to predict the results and the performances of the models are measured with AUC values and MCC (Matthew's correlation coefficient) values of the models. Predictive power of the models are as follows: MCC (Matthew's correlation coefficient) 0·29 (95% CI 0·27–0·32) and AUROC 0·75 (0·73–0·76) at admission, 0·41 (0·39–0·44) and 0·80 (0·79–0·81) after 24 h, 0·46 (0·43–0·48) and 0·82 (0·81–0·83) after 72 h, and 0·47 (0·44–0·49) and 0·83 (0·82–0·84) at the time of discharge (Thorsen-Meyer, 2020).

In 2015 Roehrig et al. carried out a study on comparison of effectiveness of three scoring systems; the stability and workload index for transfer score (SWIFT), SOFA score, therapeutic intervention scoring system (TISS-28). They have calculated SWIFT, SOFA and TISS values on the day of discharge from ICU. They have used these values in addition to length of stay and cirrhosis. They have built stepwise logistic regression models to predict mortality in 48 hours after discharge from ICU and unplanned readmission. SWIFT, SOFA and TISS-28 scores are as follows: AUC 0.65, 0.65 and 0.67, respectively, P = 0.58. All scores showed similar predictive accuracies. They have used a dataset for 1277 patients, discharged from ICU (Roehrig, 2015).

One of the early studies on predictive power of SOFA scores for length of stay of ICU patients is carried out by Antonelli et al, In 1999. They have used a dataset for 181 trauma patients. They have run a statistical analysis using SOFA values at admission and found out that a higher SOFA score and the presence of infection during the admission is correlated to higher length of stay with the following measures: additive regression coefficients: 0.85 days for each SOFA point, 4.4 for admission from the same hospital, 7.26 for infection on admission (Antonelli, 1999).

In 2016 Jain et al. conducted research on predictive power of SOFA for length of stay and mortality rates. They have used SOFA scores 24 hours after admission and SOFA scores for every 48 hours during 10 days of stay in ICU to calculate initial SOFA score, highest and mean SOFA scores which are later on used as inputs for the statistical analysis. They have found out that maximum score non-survivors is significantly lower than the number of the non-survivor population. ((3.92 ± 2.17) and (8.9 ± 3.45) respectively.) They didn't share any findings correlated to any measure of length of stay. However, they just found out that length of stay is not correlated to mortality (P= 0.461). Besides that, they didn't mention about the data size (Jain, 2016).

Converting data to images and feeding CNN algorithms with these images has been used in various fields. Kapanga et al. converted program behaviours into images and built a CNN model which is fed by these images to predict malwares (Kapanga, 2018). Sezer et al. created images from trading data and built an algorithmic trading model CNN-TA using a 2-D convolutional neural network based on image processing properties (Sezer, 2018). Yue et al conducted a study in malware binary detection via image classification (Yue, 2022). What makes our study different from these conversion methods is we search for the best conversion methodology.

3 METHODS

Following the approval of the ethical review board of University of Pittsburgh Medical Centre, which waived informed consent on the basis that this was an epidemiological study without intervention SOFA scores of 51368 patients are included in this study. Number of total data points is 2,500,000. We computed SOFA scores across six organ systems using a standard definition every eight hours throughout the ICU stays. Patients for whom there was no data to generate SOFA scores for a particular organ system are excluded. Where data to generate a score exist, but are missing at a specific time point, we linearly interpolate missing SOFA scores. Whenever the missing data is at the end of a series, we use the latest observation for the sake of refraining from extrapolation. In case of multiple entries relevant to a system score over an eight-hour interval, we choose the value generating the highest score, corresponding to the worse physiology.

One of the findings in the literature emphasizes the importance of the very early changes in organ function responses (within 1 day) in predictive model development (Levy, 2005). Therefore, we focus on first day SOFA scores to build predictive models.

3.1 Data Sources

We use the EHR-derived High Density Intensive Care (HIDENIC) database of all patients admitted to one of 12 ICUs within the University of Pittsburgh Medical Centre Health System between 2001 and 2014. HIDENIC is a HIPAA compliant, limited dataset that contains detailed demographic, diagnostic, physiologic, laboratory, and drug administration and outcome information on a source population of ICU admissions (Sileanu, 2005), (Kellum, 2015), (Sen, 2017), (Liang, 2016), linked to Social Security Death Master File (SSDMF) to 2014. The study was conducted under proper approval of the University of Pittsburgh Institutional Review Board.

3.2 Exploratory Analysis

In the data set 55% of the patients are male and 45% of the patients are female. There are 7 types of ICU admissions; 27% of patients are admitted to medical ICU, 14.5% of the patients are admitted to surgical ICU, 31% of patients are admitted to cardiac and cardiac-T units, 6.2% of patients are admitted to neurological unit, 5.5% of patients are admitted to trauma unit, 9.7% of patients are admitted to Transplant unit, and 6.1% of patients are admitted to mixed intensive care unit. Percentage of mortalities independent of which department the patients are admitted to ICU is 8.5 %, mortalities in one year after discharge from ICU is 25.8%, readmission in one year after discharge from ICU is 16.5% and length of stays for more than three days is 75.9%.

3.3 Data Preparation

We merge patients' data and the SOFA score data which we obtain from clinical measurements before admission to the ICU, during the stay in ICU, and after discharge from ICU. In our study we take into account the SOFA scores obtained from measurements after admission to the ICU and during stay in the ICU. While building the predictor models we consider the SOFA scores generated from the clinical measurements during the stay in ICU, we do not include the data before admission to ICU and after discharge from ICU. Figure 1. depicts how we prepared the data. Since the measurements are collected before ICU admission and we don't want to use the data collected before ICU admission we just take three measurement data recorded after admission to the ICU.

We approach the problem as a binary classification problem. In the exploratory analysis we noticed that the distribution of the positive (True) and negative (False) results is not balanced. Since the DATA is imbalanced, we balance data during training via oversampling for training sets of each predictive algorithm. We do not balance test data.

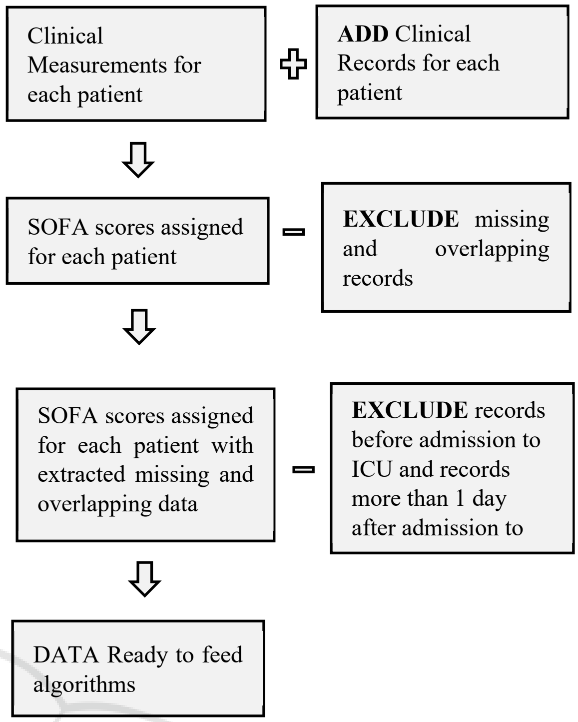


Figure 1: Data preparation process.

3.4 Machine Learning Algorithms

We use three machine learning algorithms and an ensemble of these algorithms. In addition to first three SOFA values of each category, we add an extra slope feature for each category for the predictor data set; twenty four predictors for each prediction. The number at the end of each measurement category indicates the measurement order of the relevant category; *Coagulation1* is the first measurement to derive the coagulation SOFA value after admission to the ICU, *Coagulation2* is the second measurement to derive the SOFA score after admission. We presume that the time span between each measurement is every eight hours. Predictor set for machine learning algorithms is as follows:

Input = {Liver1, Coagulation1, Nerve1, Renal1, Respiratory1, Cardio1, Liver2, Coagulation2, Nerve2, Renal2, Respiratory2, Cardio2, Liver3, Coagulation3, Nerve3, Renal3, Respiratory3, Cardio3, Change_in_Liver, Change_in_Coagulation, Change_in_Nerve, Change_in_Renal, Change_in_Respiratory, Change_in_ Cardio}

We use the random forest algorithm implemented in the Scikit-learn library. For validation and hyperparameter fine tuning we try four different hyperparameters to change: n_estimators = [10, 150, 300], max_depth= [3, None], max_features= [1, 5, 10], min_samples_leaf = [1, 25], criterion= ["gini", "entropy"]. In addition to random forest algorithm, we use Logistic Regression. We validate our model with six different set of variables keeping rest of the hyperparameters as default values. For C values we use 10^{-4}, 1, 10^{20} and for penalty function we use l1 and l2. In Support Vector Machine Algorithm, we use combinations of four different hyperparameters in the validation process: C = [1], kernel = ['linear', 'rbf'], gamma = ['scale', 'auto']. We ensembled the three previous algorithms with a hard voting classifier with best performing hyperparameters for each algorithm with their best performing hyperparameters.

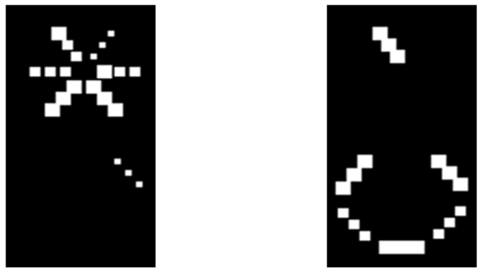
3.5 CNN

The data we have is a multivariate time series data which has six dimensions spread to points in a time line that are eight hours apart from each other. We propose various methods to convert these data into an image and train the CNN with these predictor images to find out a well performing predictive model in a binary classification problem.

We try 12 different image generation algorithms with various canvas sizes to get the best performing image data set generated from time series data. Iteratively we followed these steps till we get the best performing image set:

- Convert the time series data which has 6 variables to an identifiable image. In Figure 3. and Figure 4. Four images are displayed. These sample images represent input data for negative and positive outputs. Labels of the input images are written below the images.
- Split data to 3 sets: Train, test, validation using the proportion (0.8, 0.1, 0.1)
- Balance the training data.
- Run CNN for the training and validation data.
- Modify the training data to find out conditions which make the images more identifiable for human and which give a better CNN model performance. It is a kind of hyper-parameter fine tuning.

As seen in Figure 2. we try 69-pixel by 129-pixel images. As the SOFA score values increase the image generation algorithm brings snowflake shape at the top forefront and fades out the hexagonal shape at the bottom. As the SOFA score values decrease hexagonal shape becomes more apparent and snowflake shape fades out. The images labelled as positive usually have higher SOFA scores therefore the snowflake shape at the top becomes more apparent. The images labelled as negative usually have lower SOFA scores therefore hexagonal shapes at the bottom becomes more apparent. Since AUROC values of CNN models created using these images is less than 0.65, we keep looking for new image generation methodologies.



Positive Negative

Figure 2: Various image generation methods are used to find out the best performing image.

In Figure 3. we represent another trial we create concentric square frames on a 69-pixel by 69-pixel canvas each frame represents total SOFA score of the patient calculated for every category in every eight hours. Whiteness of the frames decreases as the SOFA score of the organ increases and greys out as the SOFA score increases. This image generation algorithm is not helpful on creatin a CNN model with high AUROC values we discarded this image generation approach.

Positive Negative

Figure 3: Image generation with concentric square frames.

After twelve trials we find out that the best performing predictor image sets can be created by following these steps:

- Create a black canvas of 69-pixel by 69-pixel
- Get the highest total score of SOFA values of six categories (Cardio, Nerve, Renal, Liver, Coagulation, Respiratory) for one day of measurements.
- Place each measurement on the -x axis of the coordinate system as a 4-pixel by 4-pixel squares, one after another in an increasing order of measurement time.

- Brightness of the squares are non-linearly proportional to the value of the SOFA scores. where m is the SOFA value and the result derived from the operation dividing m by 8 or 4 is rounded to the nearest integer value. In Yeh et al. findings patients who has qSOFA (quick SOFA) values greater than 2 has a length of stay significantly longer than patients who has qSOFA values less than or equal to 2 (Yeh, 2019). Therefore, we increase brightness of 4-pixel by 4-pixel squares which has SOFA scores greater than 2. The formula for brightness of the squares is as follows:

$$hue = \begin{cases} 255 * m/8, & m \leq 2 \\ 255 * m/4, & m > 2 \end{cases} \tag{1}$$

- Get the second highest total score of SOFA values out of the remaining five scores for one day of data.
- Place the second measurement on an axis which is sixty degrees turned from -x axis of the coordinate system in clockwise direction. Place 4-pixel by 4-pixel squares one after another in an increasing order of measurement time.
- Follow the same steps followed for the second highest total SOFA scores as well as for the third, fourth, fifth and sixth highest total SOFA scores.

As a result, in the image we get three squares placed on six axes ordered with an increasing SOFA score on each axis with an increasing order of date of measurement. In this method we take into account how many of the organs are severely damaged. You can find a typical positive and negative value image in Figure 4. One can easily notice that as the SOFA scores increase for a patient snowflake shape becomes more apparent.

Positive Negative

Figure 4: Best performing images generated for positive and negative values.

We used various batch sizes and epochs to determine the best parameters. Out of 12 different shapes best predictions are obtained by generating 69-pixel by 69-pixel images where six features are placed on six axes as apart from each other as possible. We try various CNN architectures best performance is accomplished by 4-layer CNN model. First layer has 32x3x3, second layer has 64x3x3, third layer has a 128x3x3, and fourth layer has 256x3x3 structure with each layer having (2,2) maximum pooling. We use a dense layer of 512x1 for flattening. We fine tune the hyperparameters such as epoch number, optimizer, etc. via cross validation.

4 RESULTS

We used Intel(R) Core (TM) i5-7200U CPU @ 2.50GHz 2.71 GHz with 8 GB RAM to create the models both for machine learning algorithms and CNNs. In the case of developing machine learning models computation time took between 50-200 seconds however in the case of creating CNN models computation time took between 6000-7000 seconds. Once the model is developed prediction takes less than 1 second.

The data we used was collected from 51368 patients. Out of 51368 patients 50913 patients has SOFA values recorded at least for the first day after admission to ICU. We run the five algorithms mentioned in the methods section for predicting the four predictable.

Data was imbalanced therefore we used oversampling via duplicating samples in the minority class till we get an almost even number of samples for each class. We have done the oversampling process for all the predictions and prediction algorithms.

Confusion matrixes and F1 scores for all predictions can be found in Table 1. Patients who survived ICU stay, patients who are not readmitted, patients who survived one year after discharge from ICU and patients who stayed more than 3 days in ICU are labelled as positive and patients who did not survive

Table 1: Confusion matrixes and F1 score performances of CNN models for each prediction type. TP: True Positive, FP: False positive, FN: False negative, TN: True negative.

	TP	FP	FN	TN	F1 SCORE
Mortality in ICU	3512	1150	290	142	0.83
Mortality in one year	3485	290	989	329	0.84
Readmission	4190	59	343	500	0.95
Length of Stay	2194	1674	337	888	0.68

4.1 Prediction of Mortality in ICU

Out of 50913 patients 37744, that is 91.5 % of patients survived the ICU stay. 4307, which makes 8.5 %, of them died during their ICU stay. After running the five algorithms defined in the methods section best performance is obtained by the CNN with a 0.83 AUROC (Area Under Receiver Operator Characteristics) value. Random Forest algorithm with an AUROC value of 0.72 performed slightly better than support vector machine, logistic regression and ensemble of these algorithms which has AUROC values of 0.71.

4.2 Prediction of Mortality in One Year

Out of 50913 patients 46606, which makes 74.2 % of patients, survived the first year after discharge from the ICU unit. 13169, which makes 25.8 %, of them survived the first year after discharged from the ICU unit. Best performance is obtained by the CNN algorithm with a 0.84 AUROC value. Support Vector Machine and Ensemble of Support Vector Machine, Logistic Regression and Random Forest algorithm with an AUROC value of 0.66 performed slightly better than logistic regression and Random Forest which has AUROC values of 0.64 and 0.62, respectively.

4.3 Prediction of Readmission

Out of 50913 patients 42483 which makes 83.4 % of patients readmitted in the first year after discharge from the ICU unit. 8430, which makes 25.8 %, of them are readmitted in the first year after discharged from the ICU unit. Best performance is obtained by the CNN algorithm with a 0.87 AUROC value. Support Vector Machine has an AUROC value of 0.60, Ensemble of Support Vector Machine, Logistic Regression and Random Forest has an AUROC value of 0.59, logistic regression has an AUROC value of 0.58 and Random Forest has an AUROC value of 0.55 while predicting whether patients who are discharged from ICU will be readmitted or not.

4.4 Length of Stay

We convert the problem into a binary classification problem such that whether an ICU patient would stay more than three days or less than or equal to three days. Out of 50913 patients 38672 which makes 75.9 % of patients stayed more than three days in the ICU unit. 12241, which makes 24.1 %, of them stayed less than or equal to three days in the ICU. After running five algorithms defined in the methods section best performance is obtained by the SVM algorithm with a 0.61 AUROC value. Support Vector Machine and Ensemble of Support Vector Machine, Logistic Regression and Random Forest algorithm with an AUROC value of 0.63 performed slightly better than logistic regression and Random Forest which has AUROC values of 0.58 and 0.59, respectively.

5 CONCLUSIONS

We investigated four machine learning algorithms and a CNN algorithm for predicting four features of ICU patients. The CNN model for predicting mortality in ICU, death in one year and readmission after discharge from ICU performs better than machine learning algorithms. However, ensemble of Random Forest, Logistic Regression and support vector machine classifiers performed better compared to CNN algorithm on predicting length of stay to be more than three days or less than or equal to three days.

When we compare our results with previous studies which has high predictive performances, we notice that our method performs close enough to the well performing models in the literature. For instance, we found an AUROC value of 0.83 for predicting mortality in ICU and Brito et al. predicted the mortality in ICU with an AUROC value of 0.82 via using admission SOFA scores (Brito, 2017). Aperstein et al. tried various methods with additional data such as gastrointestinal data and developed a model for predicting mortality in ICU which has a performance with AUROC values between 0.86 and 0.91 (Aperstein, 2019). Their study encourages us to generate images with additional features to improve performance of our method.

For further development and performance increase we can incorporate other features such as comorbidity and previous number of stays in the ICU units. More research can be done adding other features to calculate the hue of the squares for further research In the CNN method we use.

One of the shortfalls of our approach is generating images from temporal data which results in as a computational burden on the system. However, the images created can convey the message directly to the hospital administration. To be able to overcome this computational cost we recommend to create a well-designed data pre-processing pipeline.

In our study, best performing model is achieved after doubling the intensity of the squares for the

SOFA values higher than two as compared to SOFA values less than or equal to two. SOFA values do not have a linear proportionality in terms of severity of the patients. This finding is in accordance with the findings of Yeh et al. who found out that patients who has qSOFA values greater than 2 has a length of stay significantly longer than patients who has qSOFA values less than or equal to 2 (Yeh, 2019)

Results show that our approach could be applied to multi variate short time series problems. It can be considered as a kind of feature engineering. Number of squares in an image and the intensity of the hue in the squares can be adjusted after taking into account the domain information.

After each iteration of generating algorithm, the images are reconsidered by humans for a better performing image generation process. Therefore, it has a subjective aspect. This subjective aspect would result in both short falls and better performances in prediction.

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