Credit Default Prediction Using Bi-Directional LSTM

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1.INTRODUCTION

Financial institutions, often known as banking institutions are corporate bodies that offer services as middlemen for various financial and monetary transactions. The main function of financial institutions like a bank is to accept deposits and lend loans. Nowadays banks change their service strategies of lending loans by way of providing credit cards to the customer. Hence it can be considered one of the main income or beneficiary sources of these institutions. The banks must be considered many factors like credit score, and spending history before lending credit cards to their customers to reduce their risk of default. Banks have huge databases and proper understanding and analysis of these database results to improve performance and make progressive business decisions. The financial stability and repayment capacity of each customer varies depending on various socio-economic factors. Therefore, customers get noticeable and differential treatment based on their repayment and purchasing behaviour [1].

1.1 AIM

This paper's primary goal is to assist bank management in evaluating credit card consumers using machine learning by modelling and forecasting consumer behaviour with regard to two variables. By using the single or consecutive missed payment of credit card customers. The proposed improved model is anticipated to have the capability to effectively identify the credit default of customers to the next month by capturing meaningful patterns within consumer behaviour. The efficiency of predicting credit default is expected to be improved by leveraging the strengths of various Machine Learning techniques in combination. Preliminary investigations will be conducted to develop a credit default prediction model that solely relies on attention and transformer architecture, without employing recurrent networks for sequence processing.

1.2 OBJECTIVES

The project's initial development would be to incorporate feature selection and dimension reduction algorithms, for optimizing the process of learning classifiers. The problem with imbalanced data sets could be solved with the use of techniques like SMOTE. As a next step, LSTM recurrent neural networks will be employed as a dynamic pattern recognition classifier which would construct a context of consumer spending behaviour. LSTM feature extraction is internally taken place and is hidden from the observer. It is used for the estimation of customer behaviour scores [2].

Fine-tune the model to optimize its ability to predict customers' credit card payment behaviour and utilization rates. Evaluate the model's ability to accurately identify high-risk accounts by comparing its predictions against historical default data or external credit risk indicators. Evaluate the trained model using appropriate evaluation metrics such as accuracy, precision, recall, and F1 score. The developed LSTM model is compared with three classical machine learning algorithms: Support vector machine, Decision tree and logistic regression.

1.3 LEGAL, SOCIAL, ETHICAL AND PROFESSIONAL CONSIDERATIONS

From a legal, social, ethical, and professional standpoint, credit default prediction models raise a number of important questions. Given the usage of sensitive personal data in credit scoring, it is crucial from a legal standpoint to comply with data protection, privacy, anti-discrimination, and financial requirements. To protect people's information from unauthorised access, it is essential to guarantee data privacy and security. To stop unfair results based on race, gender, or ethnicity, it is ethically necessary to address bias and ensure fairness. For consumers to understand the motivations behind projections influencing their financial possibilities, the decision-making process of the model must be transparent and explicable. Individuals' consent must be obtained after being fully informed.

A machine learning project is more likely to be morally sound and compatible with the law. Researchers must acquire employee consent before collecting any data and inform employees of the reason for and the method for doing so. They also must make every effort to ensure that the data are accurate, securely stored, and utilised without discrimination. Additionally, if employers make it clear how machine learning can enhance the way the data operates and assist in diagnosing performance issues, employees may be more inclined to consent to the use of their data [3].

Furthermore, to guarantee reliable forecasts that do not put people in unnecessary danger, precision, dependability, and constant monitoring are crucial. Fairness, honesty, and openness in the workplace should be ensured by responsible professionals according to ethical norms. In order to provide fair financial services, it is important to take into account the wider societal impact of credit default prediction models on loan availability and financial possibilities. The main components of people participating in the creation and implementation of the models are accountability and responsibility, and they are aware of the effects of their actions. In the end, using credit default prediction models with openness, justice, and respect for moral and legal principles promotes trust as well as ethical and responsible financial behaviour.

1.4 BACKGROUND

Banks need to know whether customers are good or bad by scoring their credit and behaviour. The phrase was defined by Anderson [2] by splitting it into two parts: the first is "credit," which refers to purchasing something and paying for it later, and the second is "scoring," which is similar to the process used for credit cards. Application credit scoring, where a score is used to inform a decision on a new credit application, and behavioural scoring, which is used to address existing clients after being granted a loan, are the two main categories of credit scoring [2]. A rise in using credit cards increases the chances of missing payments because the same individual has many credit cards from different banks leading to an increase in the probability of missing payments. As a result, financial institutions are under pressure to continuously improve the system which will detect early missing payment predictions in order to mitigate substantial financial losses associated with these card transaction activities. A perfect deep-learning model needs to predict these missing payments in future.

1.5 REPORT OVERVIEW

1.5.1 Literature Review

The pros and weaknesses of various strategies are shown in this section's thorough analysis of the body of research on credit default prediction models. It highlights pertinent research using the LSTM and BiLSTM designs for related applications.

1.5.2 Technology Review

Explain how BiLSTM is different from conventional LSTM models in a quick introduction to the model's design. Declare the meaning of the term "credit default prediction" and the significance of this idea to the financial sector.

1.5.3 Methodology

The processes for data collection, preprocessing, and research design are described in the methodology section. It explains the dataset that was utilised, the characteristics that were chosen, and the justification for their inclusion. There is also extensive information on the model architecture, hyperparameter adjustment, and assessment measures.

1.5.4 Data Preprocessing

The stages of data preparation, such as cleaning the data, addressing missing values, encoding category variables, and scaling numerical characteristics, are described. It is explained how exploratory data analysis (EDA) works to understand the data distribution and spot any anomalies or trends.

1.5.5 Proposed model

The Bidirectional LSTM model's construction is explained in this section. It offers a thorough explanation of why BiLSTM was chosen over alternative architectures and illustrates how the model incorporates temporal relationships and context in both directions.

1.5.6 Performance Evaluation

In the study publication, the Credit Default Prediction Model's experimental findings are presented. Reporting includes performance measures including ROC curve analysis, recall, recall accuracy, precision, and F1-score. It is compared to baseline models and bi-directional LSTM.

1.5.7 Reference

An extensive list of references is included in the paper, including all the books, articles, and studies that were utilised to conduct the study and create the model.

2. LITERATURE REVIEW

Credit default prediction is a critical task for lender institutions to understand the risk of bankruptcy [5]. Extensive research has been conducted over decades in this area, evaluating various classification algorithms such as Logistic Regression, Decision Trees, Neural Networks, Support Vector Machines (SVM), and Least Square SVM. Studies indicate that LS-SVM and Neural Networks perform better than Logistic Regression and other linear models, making them suitable for credit scoring. Artificial intelligence techniques like Neural Networks, Support Vector Machines, and Random Forests are recommended to replace traditional credit evaluation models [5,6].

Mathematical techniques like Decision Trees, Logistic Regression, and Linear Regression are commonly used for behavioral score analysis. Including economic circumstances in scoring systems and converting default probabilities into estimates of profit or loss are also explored. Markov chain stochastic processes are employed to simulate changes in customers' credit scores and delinquent status over time, using segmentation, mover-stayer models, and higher-order models to improve model fit. Dynamic modeling is utilized to analyze the risk associated with consumer credit [7,8].

A literature review by Louzada F links theory and application of binary classification approaches for credit score analysis. The study emphasizes the significance of credit rating procedures and historical shifts in the scientific perspective [9]. Often, fixed time periods are used to calculate behavior patterns from individual transaction histories, but arbitrary value selection can lead to unstable forecasts. A study of the Irish market shows that a 12-month performance period yields better prediction results compared to other historical payment periods of varying durations. Logistic regression classifiers' performance declines significantly when the outcome window exceeds six months.

2.1 Credit cards holder’s behavioural scoring

From the above details, we can observe that there has been more focus on behavior scoring with customers' loan behavior, and behavioral scoring using credit cards has been less investigated [10]. However, some studies have explored the use of data mining techniques like Support Vector Machines, Backpropagation Neural Networks, and Linear Discriminant Analysis for behavioral scoring, with Backpropagation Neural Networks showing better overall scoring accuracy [11].

In credit behavioral scoring, timing the time to default is discussed to include a dynamic component in models, and neural networks are compared with survival analysis to improve default predictions [12]. Furthermore, survival analysis has been utilized to simulate credit card account default and incorporate macroeconomic variables to enhance model fit and default predictions [13]. Dynamic models that consider behavioral and macroeconomic factors have shown significant improvements in default forecasts [13].

The use of mail-in questionnaires in credit card customer studies revealed that attitudes and personality factors were correlated with credit card usage. Certain credit card features could lead to an "illusion of income," encouraging credit card debt [14]. Big data and social data, such as Weibo user behavior information, have been used to evaluate creditworthiness and determine credit scores [15].

2.2 Machine Learning approaches in behavioural Scoring

In the current era, the usage of credit cards is increasing day by day, leading to a substantial increase in transaction datasets. Handling such big data using conventional statistical and mathematical models has limitations. Particularly, behavioral scoring requires a significant amount of transactional data, which has received less attention compared to application scoring due to data biases and economic sensitivities associated with consumer data [16]. Bastani K's studies present a two-stage scoring system for choosing the best loans for investment, focusing on probabilities of default (PD) prediction and profitability prediction [17].

2.2 TECHNOLOGICAL LITERATURE

Following are the technological developments that happened in the area of Bidirectional LSTM during recent years.
Bidirectional LSTMs are capable of capturing both forward and backward dependencies in sequential data, making them ideal for modelling intricate spending patterns. Time-series financial data, such as credit card transactions, have demonstrated exceptional performance in capturing long-term dependencies using Bidirectional LSTMs.

The bidirectional LSTM exhibits resilience to noisy data, making it a suitable choice for dealing with scenarios where there are missing transactions or incomplete card usage patterns. In order to compensate seamlessly for missing data, Bidirectional LSTM captures the underlying dynamics of sequences effectively [18].

In comparison to other sequential data modelling approaches, Bidirectional LSTM has demonstrated improved accuracy in modelling credit card usage patterns. Its capacity to capture information from sequences both in the forward and backward directions contributes to its superior performance [19].

The banking industry relies heavily on real-time analysis of credit card usage to meet its risk management objectives. The computational efficiency of Bidirectional LSTM, relative to traditional neural networks, enables its utilization in real-time credit card usage analysis by banks.

Bidirectional LSTM facilitates the incorporation of external data sources, such as demographics, geographic locations, and transaction amounts, to improve the modelling and prediction of customers' credit card usage. This capability enhances the overall accuracy and predictive power of the model.

2.2.1 Benchmark Models

The scoring quality of machine learning models for classification is negatively impacted when dealing with high-dimensional datasets. Classification methods like Support Vector Machine, Decision Tree, and Logistic Regression are effective but time-consuming during training [20]. Feature extraction from datasets can lead to information loss. Considering these factors, neural networks, particularly bidirectional LSTM, offer better performance without the need for specific feature tasks [21]. In this study, conventional machine learning algorithms (SVM, decision trees, random forests, and logistic regression) are compared with bidirectional LSTM for predicting credit defaults, evaluating accuracy and performance.

2.2.1.1 Support Vector Machine

An innovative machine learning technique called an SVM is also used to solve problems with credit rating and order. By modifying the design of a linear classifier, Cortes and Vapnik [22] first developed SVMs. The function that is utilised to translate the data into a higher dimensional space is the main difference between the SVM model and the linear one. The following kernel functions were proposed to do this: linear, polynomial, radial basis, and sigmoid. A linear model is then utilised to implement the non-linear classes from the mapped high-dimensional feature space of two classes of non-linear data produced by an SVM. SVMs are efficient in high-dimensional spaces and are thus appropriate for situations with many characteristics. SVMs strive to maximise the margin between classes, which aids in the creation of a decision boundary that generalises well to untried data. This makes SVMs robust against overfitting.

2.2.1.2 Logistic Regression

For the creation of credit scoring models, logistic regression (LOGR) has been regarded as the industry standard up to this point [22]. This widely used statistical method is well-liked for resolving classification and regression issues. A binary outcome variable, often denoted by 0 or 1 (good and bad loans), is modelled using LOGR. Atiya and Palos [23] provide the LOGR formula.

Due to its suitability for binary and multi-class classification tasks, logistic regression is employed in classification since it models the chance of an instance belonging to a certain class. Making decisions is aided by the logistic (sigmoid) function's guarantee that the anticipated probability fall between 0 and 1.

2.2.1.3 Decision Tree

According to Bierman’s [24] proposal, a random forest (RF) is a novel decision tree (DT) technique that consists of a lot of trees made from n subsets of the core dataset, each of which is a tree made up of randomly chosen variables, hence the name "random forest." The final decision class is based on a voting process, where the RF chooses the most well-liked class determined by the trees as the final output class once all the DTs have been formed and trained.

Due to its interpretability and capacity for handling complicated decision boundaries, decision tree algorithms are employed for categorization. They produced a tree-like structure by iteratively dividing the data depending on the feature values. This helps make decision-making processes understandable, which makes it useful for both straightforward and hard categorization jobs.

2.2.1.4 Bidirectional LSTM

The recurrent neural network is a powerful model for sequence data and good for labelling input and output labelling if the labelling is unknown for classification problems. The combination of a Recurrent neural network with long short-term memory is considered to be more fruitful [25]. The performance of bidirectional LSTM is good compared to unidirectional LSTM and conventional recurrent neural networks. Bidirectional neural network process input data in both forward and backward directions and hence can process both current and future data [26].

Directed cycles are created via connections between cells in a recurrent neural network. A hidden state is present in each cell and is updated with each iteration using its previous values. Such a structure serves as a memory and establishes an internal network state.

The RNN equations are as follows:

$$\begin{cases} S_t = f(U \cdot x_t + W \cdot s_{t-1}) \\ h_t = g(V \cdot s_t) \end{cases}, \qquad (1)$$

x = input vector, s = hidden vector of RNN layer values, h = output vector of RNN layer values, U = weight matrix from the input layer to hidden layer, V = weight matrix from hidden layer to the output layer, W = weight matrix from previous time point to current time point of hidden layer, and g and f = activation functions for output and hidden layers. The function of one RNN cell is shown in Fig. 1. We feed the cell the time series signal X one element at a time. Te vector X may be output from another vector or an input vector. From the preceding layer, RNN cell. Te RNN cell keeps its current state. Eq. (1) is used to determine the state st and output ht at each iteration t. RNNs' design enables them to [27]: Learning long-term reliance, meanwhile, has its challenges. It is challenging to understand long-term dependencies because RNN is prone to disappearing gradients during training [28]. An LSTM based on RNN has been presented by Hochreiter and Schmidhuber [29] as a solution to this issue. Similar to RNNs, the experience of the network's inputs always influences how well LSTM predictions perform.

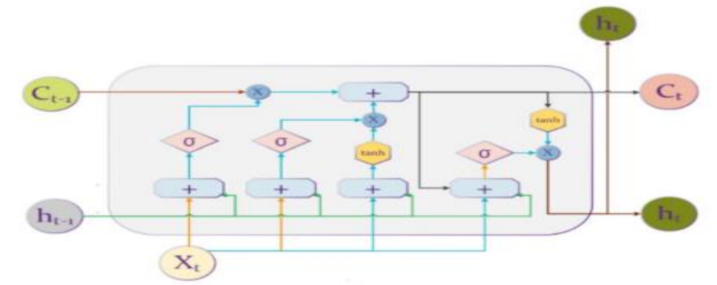

Fig. 2 LSTM model structure [21]

Figure 2 depicts the structure of a single LSTM cell. An input gate, which regulates how many cell states must be stored, is one of the three gates that make up an LSTM cell, as shown in Figure 2. A forget gate, which regulates how much information has to be deleted, and an output gate, which regulates how many cell states are transferred to the following cell must [30]. Internal states may be found in two of these gates. As can be observed, the LSTM cell calculates the candidate vector Ct1 and output vector ht1's subsequent values using the vectors' prior values on each iteration t. Activation functions are used to post-process each gate's output. The activation function's form is

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

The output gate of an LSTM cell uses the hyperbolic tangent function by default. The range of values for the smooth antisymmetric hyperbolic tangent function, tanh, is [1, 1]. The tanh function's output is represented by:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (3)$$

Tanh's key benefit is that it generates zero-centred output, which facilitates the back-propagation process. The specific steps of an LSTM cell are described as follows:

LSTM should choose which knowledge to forget in the first stage. For this reason, the forget gate ft is used to process the data from the prior memory state.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (4)$$

Input gates it determines which data has to be updated on the second step, and the tanh layer updates the candidate vector C t:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \quad (6)$$

The following step involves updating memory states Ct in order to combine the two elements above:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (7)$$

Finally,

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

$$h_t = o_t \times \tanh(C_t) \quad (9)$$

As a result, each LSTM layer is [38] characterised by:

(1) Matrix Wf and bf, vector, which are the forget gate's parameters
(2) The parameters of the input gate are the matrix WC and the vector bC, and
(3) The parameters of the output gate are the matrix Wo and the vector bo.

Bidirectional LSTM neural networks were suggested in the research [31] as a way to improve the functionality and learning rate of LSTM neural networks. Bidirectional LSTMs are an extension of conventional LSTMs that can enhance model performance on sequence classification issues, according to Schuster and Paliwal. Bidirectional LSTMs train two LSTMs rather than one on the input sequence in instances where all time steps of the input sequence are known. First on the original input sequence, then on a reversed replica of the original input sequence. This can provide the network extra context and lead to a quicker and even more thorough learning process for the problem.

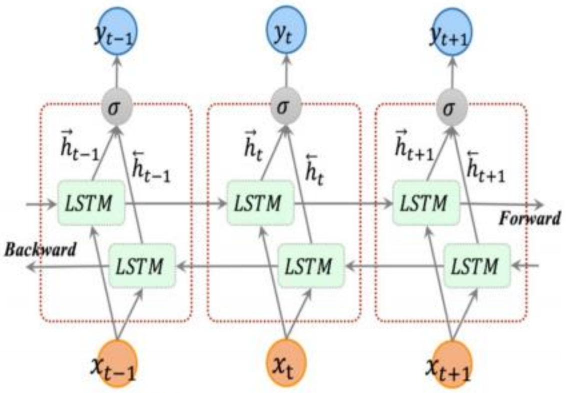

Fig. 3 Bidirectional LSTM architecture [53]

According to fig-3, The forward layer output sequence, h, is computed iteratively using inputs in a positive sequence from time t = 0 to time t = T, whereas the backward layer output sequence, is calculated using inputs in a negative sequence.

h is computed using the inputs from time t = T to t = 0 in reverse order. The conventional LSTM updating equations, Eqs. (2–7), are used to compute the forward and backward layer outputs. The output vector, Yt, that the Bidirectional LSTM layer produces has each element computed using the equation below:

$$y_t = \omega\left(\overrightarrow{h}_t, \overleftarrow{h}_t\right), \quad (10)$$

3.METHODOLOGY

In the recent work from Maher Alaraj [2] and coworker we have seen that they divide input data into two temporal and non-temporal data where temporal data shows customer behaviour in time and which reshaped into a three-dimensional array of shapes. Non-temporal having some overlaps to statics features. Static data having both numerical and categorical. In this dataset context, data having a specific type of static feature also hence they feed non-temporal data into a dense layer of LSTM and temporal data into bidirectional LSTM. Here I am analysing the same dataset and it is fed into bidirectional LSTM without splitting the data into temporal and non-temporal. Apply SMOTE technique to eliminate the basic behaviour of overfitting from the dataset and analysis its performance with support vector machine, logistic regression, and decision tree algorithms.

The general model framework of the methodology is shown in fig-4.

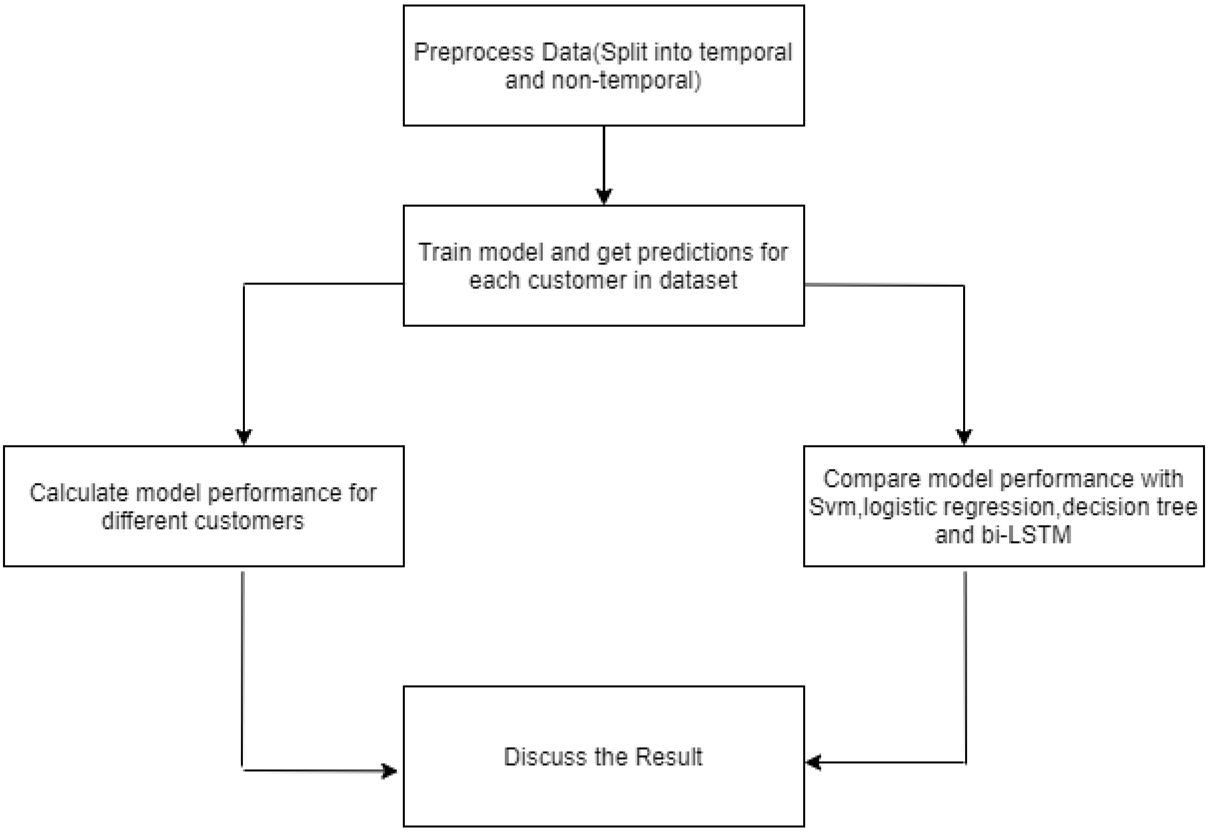

Fig.4 Model frame

3.1 Data collection

The dataset collected for this credit default prediction using deep learning task is an open source or public non transactional credit cards dataset. It shows customers default payment in Taiwan [32]. Usually, banks do not disclose transactional databases in original form, mostly there are appeared to be processed forms. Hence, we are using this dataset because this is the only publicly available dataset that can convert to temporal form.

The size of the dataset is 30,0000 records and has 23 variables. It is enough for test accuracy, precision, recall, and F1-Score. The number of non-default payments is 23,364 and the default payment is 6636. There is no missing value in the dataset. The attributes of this dataset are:

1. X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.
2. X2: Gender (1 = male; 2 = female).
3. X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).
4. X4: Marital status (1 = married; 2 = single; 3 = others).
5. X5: Age (year).

6. **X6 - X11**: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows:
7. X6 = the repayment status in September, 2005;
8. X7 = the repayment status in August, 2005; . . .;
9. X11 = the repayment status in April, 2005. The measurement scale for the repayment status is: -1 = pay duly; 1 = payment delay for one month; 2 = payment delay for two months; . . .; 8 = payment delay for eight months; 9 = payment delay for nine months and above.
10. **X12-X17**: Amount of bill statement (NT dollar).
11. X12 = amount of bill statement in September, 2005;
12. X13 = amount of bill statement in August, 2005; . . .;
13. X17 = amount of bill statement in April, 2005.
14. **X18-X23**: Amount of previous payment (NT dollar).
15. X18 = amount paid in September, 2005;
16. X19 = amount paid in August, 2005; . . .;
17. X23 = amount paid in April, 2005.

3.2 Preprocessing and Exploratory Data Analysis

3.2.1 Label Encoding

Label encoding is a preprocessing technique used for converting categorical values into numerical ones. It makes data to be ready for the training process. Reduces memory usage as compared to the one-hot encoding. Which replaces a single categorical column with a single numerical column.

3.2.2 Feature Scaling

Since there are no missed values, we can apply feature scaling to check whether all features are on the same scale. Which should be beneficial for machine learning algorithms. Normally we are using Min-max Scaling or standardization technique. In min-max scaling the values range between 0 and 1.

Min-max scaling, also known as normalization, is a common data preprocessing technique used in machine learning and statistics. It is applied to rescale the values of a numerical feature within a specific range, typically between 0 and 1.

The formula is as:

Scaled Value= (Max Value−Min Value)/ (Original Value−Min Value)

- "Original Value" denotes the actual value of the data point.

- "Min Value" refers to the feature's lowest value throughout the whole dataset.

- "Max Value" refers to the feature's highest possible value throughout the whole dataset.

3.2.3 Data Cleaning

There is no missing value to handle and outliers are removed in this step.

3.2.4 Exploratory Data Analysis

Exploratory Data Analysis is very crucial for a dataset. Which gives valuable insights into the data from a dataset. It also shows the characteristics of the data like data overview, class imbalance temporal aspects etc. Proper visualization of the data from a dataset gives a deep understanding of data in exploratory data analysis.

a) Visualization of target variable distribution in credit default prediction?

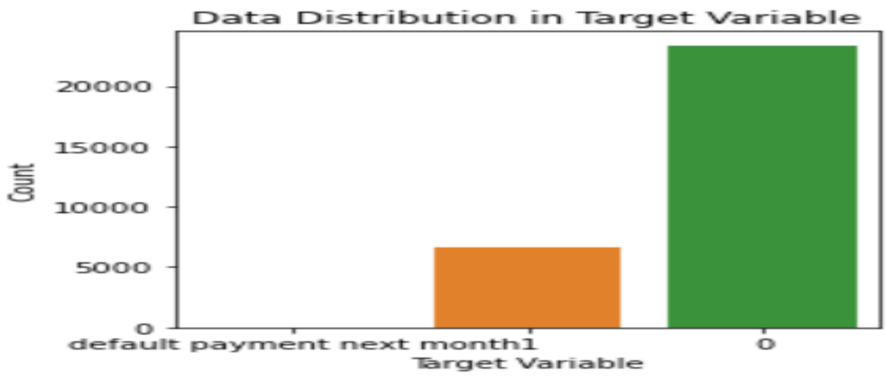

Fig.5 Target variable distribution

b) Boxplot representation of the dataset give outlier information?

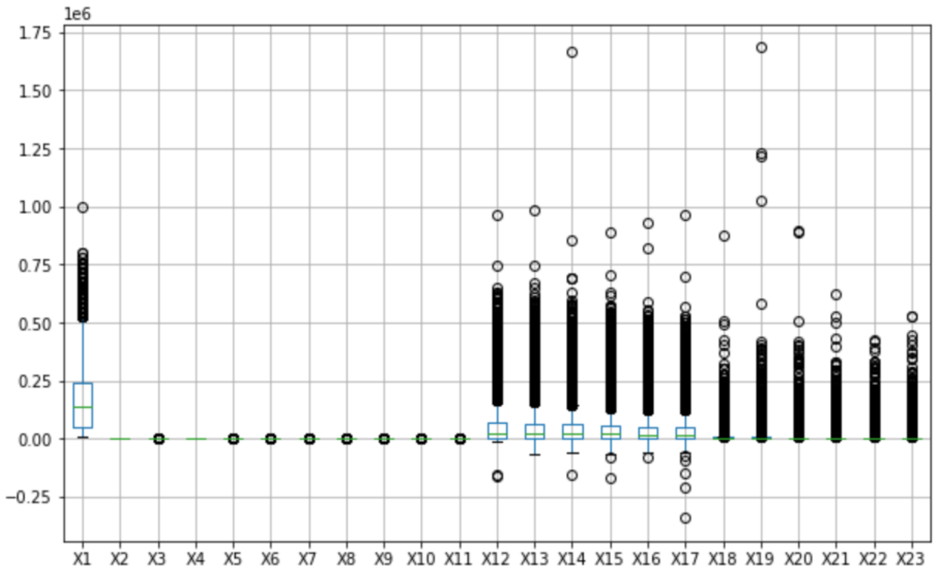

Fig.6 Outlier Representation

d) Histogram representation of some variables?

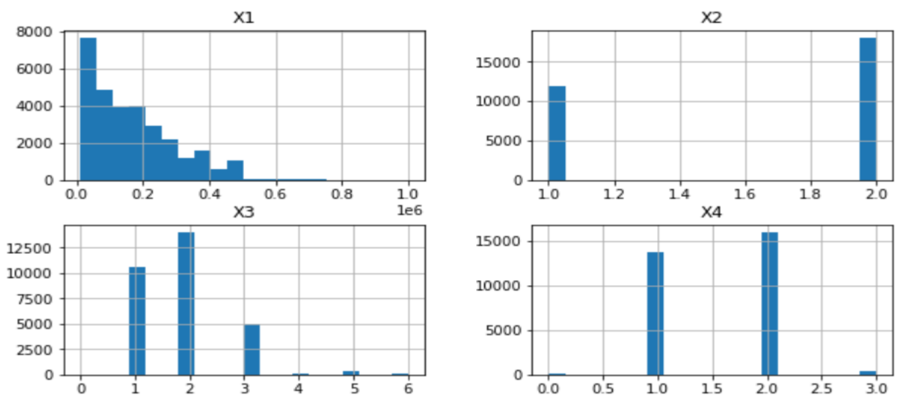

Fig.7 Histogram Representation of Attributes

c) Heatmap showing the correlation between the attributes?

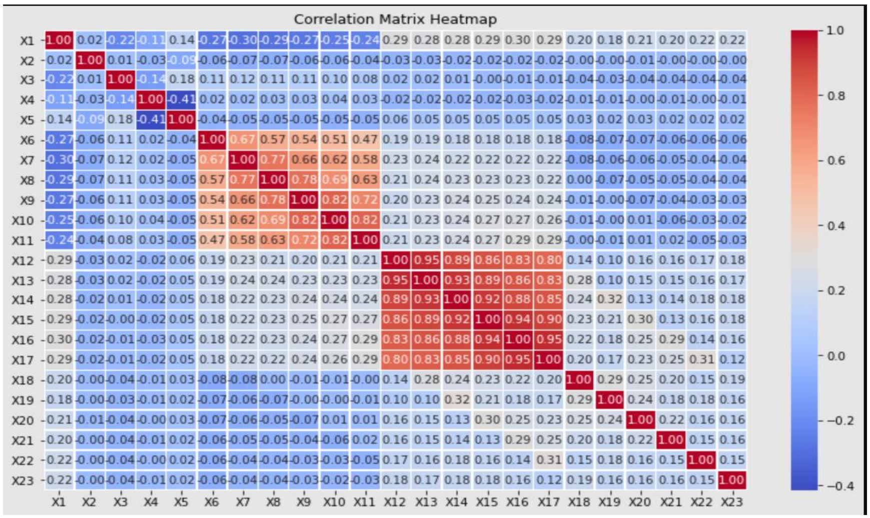

Fig.8 Heatmap showing Corelation

3.3 Data Splitting

Splitting the data into training and testing sets is known as data splitting. The model is trained using a training set, and its performance on testing data is assessed.

3.4 Feature Selection

For the job of predicting credit defaults, choose the features that are most pertinent. The choice of features can improve model performance by lowering noise. In case of conventional algorithm like support vector machine, logistic regression and decision tree algorithm we need feature extraction as the main step but in the case of deep learning, we don't need to accomplish this step because the feature is taken internally.

3.5 Handling class imbalance

SMOTE is only used on the training set when there is a class imbalance in the dataset, meaning that the minority class is underrepresented. SMOTE creates synthetic samples for the minority class, distributing the classes more evenly.

3.6 Model Training

Training the model with conventional algorithms like support vector machine, Logistic Regression and decision tree are taken place. Compare the performance of these algorithms with a deep learning algorithm named bidirectional LSTM.

3.7 Proposed Model

Deep learning frameworks such as TensorFlow or PyTorch make it simple to create bidirectional LSTMs. These frameworks provide layers and built-in functions for constructing bidirectional LSTM networks and training them on diverse tasks. An alternative to the Long Short-Term Memory (LSTM) neural network design is the Bidirectional Long Short-Term Memory (BiLSTM). A conventional LSTM processes the input data sequence from start to finish while maintaining a hidden state that stores knowledge from the previous context. The context provided by upcoming data pieces, however, may occasionally also be helpful in formulating precise forecasts. Bidirectional LSTM can be used in this situation. A bidirectional LSTM processes the input sequence in two different directions: forward (from beginning to finish) and backwards (from end to beginning). Two distinct sets of hidden states are kept throughout training and prediction. Here the data is not sequential but here nature of the data is temporal which is why we are using bidirectional LSTM [42].

Here the data from the dataset is directly fed into Bi-directional LSTM and the performance is analysed and compared against other conventional algorithms mentioned. The proposed model of bi-directional LSTM can be represented in fig-5.

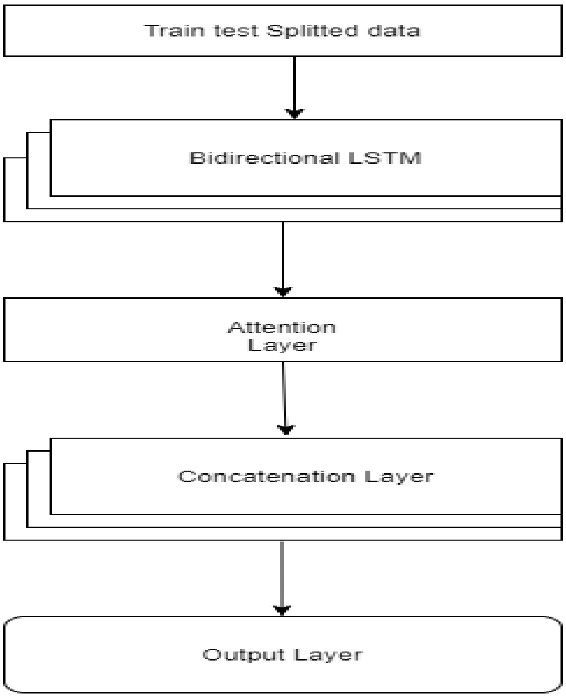

Fig.7 General data Flow in Bi-directional LSTM in credit default prediction

As in Fig.7, The first two layers are bidirectional LSTM.Here temporal and non-temporal fed together into the bi-directional LSTM.Next Layer is attention layer, with the use of an attention mechanism, the model may be taught to concentrate on crucial input sequence segments while generating predictions. The last two layers concatenate the output and having one neuron. The number of neurons in each layer are selected using grid search, activation functions [42]. The performance is analysed and compared with conventional algorithms.

3.8 PROJECT MANAGEMENT TOOL

Project management tools like Teamwork and GitHub are used in order to get proper version control over the project. The corresponding links are: -

Teamwork link

https://universityofroehampton15.teamwork.com/app/home/projects

GitHub link

https://github.com/Meritc/Data-Science

Project Report Delivery Schedule Note: Reorder the sections in the order that you plan to complete them.	Deadline Date
Abstract	06/08/2023
Declaration	07/08/2023
Acknowledgements	07/08/2023
Introduction	08/08/2023
Literature - Technology Review	10/08/2023
Methodology	12/07/2023
Implementation and Results • Evaluation • Related Work	23/08/2023
Conclusion • Reflection • Future Work	24/08/2023
References	25/08/2023
Appendices	25/09/2023

Artefact Delivery Schedule Note: Reorder the activities in the order that you plan to complete them.	**Deadline Date**
Artefact Planning and Resourcing	27/07/2023
Artefact Design	31/07/2023
Artefact Procurement Activities (e.g., data collection, source framework etc.)	01/08/2023
Artefact Development, Deployment, Implementation	10/08/2023
Artefact Evaluation and Testing	25/08/2023
Artefact Presentation and Demonstration	06/09/2023
Artefact Screencast	06/09/2023

4. PERFORMANCE EVALUATION

It is essential to evaluate the performance of credit default prediction models in order to determine how well they forecast consumer behaviour and spot possible defaulters. The effectiveness of such models may be evaluated using a number of assessment indicators. These measurements are some of the most popular.

Accuracy: By comparing the proportion of accurate forecasts to all other predictions produced, accuracy assesses how accurate the model's predictions are overall. However, accuracy by itself could not give a whole picture, particularly if the data are unbalanced (i.e., the proportion of defaults to non-defaults is substantially smaller).

Precision: Out of all occurrences anticipated to default, precision represents the percentage of accurately predicted defaults. It focuses on how trustworthy the optimistic forecasts are. A low false positive rate is shown by high accuracy, which means that the majority of anticipated defaults are accurate.

Recall (Sensitivity or True Positive Rate): Recall calculates the percentage of expected defaults that really occur that were right. It emphasises the model's capacity to locate genuine positives. A low false negative rate is shown by a high recall, which means that the majority of real defaults are found.

F1 Score: The harmonic mean of recall and accuracy is the F1 score. It offers a fair assessment of both measurements and is particularly helpful in cases where the data is unbalanced. A high F1 score suggests that accuracy and recall are well-balanced.

Receiver operating characteristic area under the curve (AUC-ROC): The trade-off between true positive rate (TPR) and false positive rate (FPR) at different classification thresholds is represented by the ROC curve. The model's capacity to differentiate defaulters from non-defaulters across various thresholds is measured by AUC-ROC. Better model performance is indicated by higher AUC-ROC values.

Confusion matrix: This gives an explanation of model performance and displays true positives, true negatives, false positives, and false negatives. It may be used to determine a number of performance parameters, including F1 score, recall, accuracy, and precision. It cannot be used for regression problems.

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