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Adaptive One-Dimensional Convolutional Neural Network for Tabular Data

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Abstract— This study introduces an innovative approach for tackling the credit risk prediction problem using an Adaptive One-Dimensional Convolutional Neural Network (1D CNN). The proposed methodology is designed for one-dimensional data, such as tabular data, through a combination of feed-forward and back-propagation phases. During the feed-forward phase, neuron outputs are computed by applying convolution operations to previous layer outputs, along with bias terms and activation functions. The subsequent back-propagation phase updates weights and biases to minimize prediction errors. A custom weight initialization algorithm tailored to Leaky ReLU activation is employed to enhance model adaptability. The core of the proposed algorithm lies in its ability to process each training data sample across layers, optimizing weights and biases to achieve accurate predictions. Comprehensive evaluations are conducted on various machine learning algorithms, including Gaussian Naive Bayes, Logistic Regression, ensemble methods, and neural networks. The proposed Adaptive 1D CNN emerges as the top performer, consistently surpassing other methods in precision, recall, F1-score, and accuracy. This success is attributed to its specialized weight initialization, effective back-propagation, and integration of 1D convolutional layers.

Keywords- Convolutional Neural Network; activation function; one dimensional data; back propagation; bias

I. INTRODUCTION

In today's data-driven world, accurate and reliable credit risk prediction [1]–[4] is of paramount importance for financial institutions and lending organizations. It not only safeguards against potential financial losses but also ensures responsible and fair lending practices [5], [6]. Traditional methods of credit risk assessment [2], [7] have seen a significant evolution with the advent of machine learning and deep learning techniques [4], [8], and one such innovation is the Adaptive One-Dimensional Convolutional Neural Network (1D CNN).

This study introduces a novel approach to tackle the credit risk prediction problem by harnessing the power of deep learning, specifically tailored for one-dimensional data such as tabular data. The proposed methodology combines the principles of feed-forward and back-propagation phases, creating a robust framework capable of adapting and optimizing its parameters to achieve precise predictions.

In the feed-forward phase, neuron outputs are computed by applying convolution operations to the previous layer outputs, incorporating bias terms and activation functions. This process is crucial in capturing complex relationships and patterns within the data. Subsequently, during the back-propagation phase, the model fine-tunes its weights and biases to minimize prediction errors, ensuring continuous improvement in performance.

A key innovation of this approach lies in its custom weight initialization algorithm, specifically designed to enhance the adaptability of the model, particularly when using the Leaky ReLU activation function. This initialization method ensures that the model starts with optimal weight values, expediting the training process.

To assess the effectiveness of the proposed Adaptive 1D CNN, a comprehensive evaluation is conducted, comparing it against various machine learning algorithms, including Gaussian Naive Bayes, Logistic Regression, ensemble methods, and neural networks. The results reveal that the proposed algorithm consistently outperforms its counterparts across multiple performance metrics, including precision, recall, F1-score, and accuracy.

This study not only highlights the superior performance of the Adaptive 1D CNN but also underscores the importance of leveraging deep learning techniques in credit risk prediction tasks. By embracing innovative approaches like this, financial institutions can make more informed lending decisions, minimize risks, and ultimately contribute to the stability and responsible functioning of the financial ecosystem. The remainder of this paper delves into the Literature review, methodology, results, and discussions, providing valuable insights into the potential applications of this adaptive neural network in the domain of credit risk assessment.

II. LITERATURE REVIEW

Credit risk prediction is a critical task in the financial industry, and researchers have explored various methodologies to enhance its accuracy and reliability [9]–[12]. This literature review provides an overview of key developments in credit risk assessment and contextualizes the proposed Adaptive One-Dimensional Convolutional Neural Network (1D CNN) within the existing body of research.

Machine learning approaches have brought significant improvements to credit risk assessment. Random Forest and Gradient Boosting models, have exhibited remarkable predictive power. These ensemble methods [5], [13], [14] can capture intricate interactions in the data, resulting in superior performance [15]–[19]compared to traditional models.

Deep learning techniques have also gained traction in credit risk prediction [20]–[23]. Multi-layer perceptrons (MLPs) [24] and recurrent neural networks (RNNs) [25] have been applied to credit scoring tasks. Various studies explored the use of MLPs for credit risk assessment and demonstrated competitive results. However, these architectures may not be optimized for tabular data, where the sequential nature of data is less evident.

One-Dimensional Convolutional Neural Networks (1D CNNs) [26]have recently emerged as promising tools for processing one-dimensional data, making them well-suited for tabular datasets. In natural language processing, 1D CNNs have excelled in tasks involving sequential data. The ability of 1D CNNs to capture local patterns and hierarchies makes them appealing for financial data analysis. Various researchers applied 1D CNNs to financial data, demonstrating their adaptability to this domain.

The proposed Adaptive 1D CNN framework builds upon the strengths of 1D CNNs while addressing specific challenges in credit risk prediction. One such challenge is custom weight initialization [27], [28]. Weight initialization is crucial for the convergence of neural networks, and custom initialization methods tailored to activation functions have been proposed in the literature.

Ensemble methods, such as Extra Trees and Random Forest, have been successful in mitigating overfitting and improving model generalization in credit risk prediction. These ensemble techniques often combine multiple models to make more accurate predictions. While highly effective, their performance can vary due to their inherent randomness.

Interpretable models [29]–[31], such as logistic regression, remain relevant in credit risk assessment due to their transparency and regulatory compliance. The interpretability vs. performance trade-off is a crucial consideration in real-world applications, where stakeholders demand not only accurate predictions but also comprehensible explanations for those predictions.

Credit risk prediction has evolved from traditional statistical models [3], [32]–[35] to embrace the power of machine learning and deep learning techniques [36]–[38]. The proposed Adaptive 1D CNN framework leverages the capabilities of 1D CNNs and custom weight initialization to address specific challenges in credit risk assessment. This literature review underscores the importance of continuous innovation in credit risk prediction [39]–[42] to meet the demands of modern finance while adhering to regulatory [43] and ethical standards. The subsequent sections of this study provide empirical evidence of the effectiveness of the proposed approach in addressing these challenges.

III. METHODOLOGY

The proposed 1D-CNN framework involves both forward and backward phases to process one-dimensional data. The feed-forward phase computes neuron outputs by combining bias terms and the results of convolution operations, followed by activation. The back-propagation phase minimizes prediction errors by updating weights and biases based on error derivatives. The custom weight initialization algorithm tailors weight initialization to Leaky ReLU activation. Together, these components enable the training and optimization of an adaptive 1D-CNN model for various one-dimensional data tasks.

In the proposed 1D-CNNframework, during the feed-forward phase, the input ψ of a neuron on a layer ϑ is denoted as follows:

$\xi_{\psi}^{\vartheta} = \gamma_{\psi}^{\vartheta} + \sum_{i=1}^{\nu_{\vartheta-1}} \text{conv1D}\,(w_{i\psi}^{\vartheta-1}, \sigma_{i}^{\vartheta-1})$

where $\gamma_{\psi}^{\vartheta}$ represents the bias for the neuron ψ on layer ϑ. The convolution operation is performed iteratively over layers from the first to ϑ – 1, considering the kernel weights w and output σ from the neuron ψ on layer ϑ - 1. The intermediate output corresponding to ξ_{ψ}^{ϑ} is transformed using a function α to yield:

$\sigma_{\psi}^{\vartheta} = \alpha(\xi_{\psi}^{\vartheta})$

where $\sigma_{\psi}^{\vartheta}$ is the direct implication of ξ_{ψ}^{ϑ} with function α. Here, the function α encompasses multiple operations, potentially including softmax, sub-sampling, and flattening.

During the back-propagation phase, the primary goal is to minimize the squared summation of discrepancies between the output $\sigma_{\psi}^{\vartheta}$ and the target υ_{i}^{q} which is expressed as:

$$\sum_{i=1}^{\nu_{\vartheta}} (\sigma_{i}^{\vartheta} - \upsilon_{i}^{q})^2$$

The convergence of the 1D-CNN occurs naturally through a sequence of iterations, leading to the determination of optimal weights and biases. The comprehensive approach of the proposed adaptive 1D-CNN is outlined in Algorithm 1:

Algorithm 1: Algorithm proposed 1D-CNN

Input: ξ_{ψ}^{ϑ}
Target: $w_{i\kappa}^{\vartheta-1}$, $\gamma_{\kappa}^{\vartheta}$
Initialization: Custom_Weight_Initialization()
Feed forward phase:
for All $\xi \in$ X do
$\forall\psi \in [1, \nu_{\vartheta}]$, $\forall\psi \in [1, \Omega]$: $\sigma_{\psi}^{\vartheta} = \alpha(\xi_{\psi}^{\vartheta})$;
$\varepsilon = \sum_{i=1}^{\nu_{\vartheta}} (\sigma_{i}^{\Omega} - \upsilon_{i}^{q})2$;
Back-propagation phase
$w_{i\kappa}^{\vartheta-1}(t+1) = w_{i\kappa}^{\vartheta-1}(t) - \text{diff}(\varepsilon)$; $\gamma_{\kappa}^{\vartheta}(t+1) = \gamma_{\kappa}^{\vartheta}(t) - \text{diff}(\varepsilon)$;
end for

The proposed 1D-CNN algorithm takes the inputs as every training data sample ξ of every neuron ψ on layer ϑ, namely, ξ_{ψ}^{ϑ}. It seeks to determine the optimal weight from the previous layer, $w_{i\kappa}^{\vartheta-1}$ and the bias at the current layer $\gamma_{\kappa}^{\vartheta}$. At the initialization, all weights are initialized using custom function. For every $\xi \in$ X, the feed-forward propagation computes $\sigma_{\psi}^{\vartheta}$, $\forall\psi \in [1, \nu_0]$ and $\forall\vartheta \in [1, \Omega]$. The prediction error is calculated by comparing the difference between $\sigma_{\psi}^{\vartheta}$ and υ_{t}^{q}. In the back-propagation stage, the weights and biases are updated based on the derivative of the error, denoted as diff (ε).

The Custom_Weight_Initialization() bounds and generate random values for the weight tensor using a custom initializer specifically tailored for the Leaky ReLU activation function. The algorithm ensures that the weights are initialized within a range that takes into account the Leaky ReLU slope parameter (alpha) and fan_in.

Algorithm: Custom_Weight_Initialization

Input: Shape of the weight tensor (shape), desired dtype (dtype)

1. Initialize alpha = 0.01 (Leaky ReLU slope for negative values)
2. Calculate fan_in as the number of input units in the weight tensor (shape[0])
3. Calculate limit = sqrt(2 / fan_in) * sqrt(1 + alpha^2)
4. Generate random values for the weight tensor within the range [-limit, limit] using a uniform distribution:

- Create an empty tensor (initializer) with the specified shape and dtype
- For each element (i, j) in the tensor:
  - Generate a random value using a uniform distribution U(-limit, limit)
  - Assign the random value to the element (i, j) of the tensor

5. Return the initialized weight tensor (initializer)

Output: Initialized weight tensor for the Leaky ReLU activation function.

IV. RESULTS AND DISCUSSION

Table 1: Performance Comparison of Proposed Model

Algorithm	Precision	Recall	F1-score	Accuracy
Gaussian NB	93.740	85.833	89.2	86.310
Logistic Regression	95.420	96.411	95.734	96.605
Extra Trees	94.512	87.741	89.821	96.204
Random Forest	96.231	96.322	95.413	96.903
XGB	97.330	97.214	96.542	97.130
LGBM	96.102	96.632	95.323	97.044
Neural Network	91.843	95.501	93.931	96.424
Proposed Algorithm (Multistage 1 D CNN)	**99.401**	**99.213**	**99.302**	**99.142**

The table 1 presents an in-depth evaluation of various machine learning algorithms based on key performance metrics: Precision, Recall, F1-score, and Accuracy. These metrics collectively shed light on the algorithms' capabilities in making accurate predictions and capturing positive instances in a credit risk prediction task. The proposed algorithm outperformed all other classification algorithms.

Starting with the Gaussian Naive Bayes algorithm, it achieves a precision of 93.740, signifying that when it predicts a positive class, it is correct approximately 93.74% of the time. However, its recall, at 85.833, reveals that it may miss around 14.17% of actual positive cases. The F1-score of 89.2, which considers both precision and recall, demonstrates an overall performance balance. The algorithm's accuracy stands at 86.310, indicating its correctness in classifying instances.

In the case of Logistic Regression, the precision of 95.420 indicates a strong accuracy in positive predictions. The high recall of 96.411 suggests that the algorithm captures a substantial number of true positive cases. The F1-score of 95.734 further consolidates the algorithm's balanced precision-recall performance. The accuracy of 96.605 underscores its proficiency in accurately classifying instances.

Moving on to the Extra Trees algorithm, the precision of 94.512 implies a reliable positive prediction ability. However, the recall of 87.741 indicates that it might overlook a portion of actual positive cases. The F1-score of 89.821 offers an overall evaluation of its precision and recall, while the accuracy of 96.204 highlights its general correctness in classification.

The Random Forest algorithm demonstrates a precision of 96.231, indicating its accuracy in positive predictions. With a recall of 96.322, it effectively captures a significant proportion of actual positive instances. The F1-score of 95.413 represents a harmonious blend of precision and recall, while the accuracy of 96.903 reinforces its capability in accurate classification.

The XGBoost algorithm's precision of 97.330 showcases its strong accuracy in predicting positive instances. The recall of 97.214 indicates its proficiency in capturing most true positive cases. The F1-score of 96.542 underscores its balanced precision-recall performance. The high accuracy of 97.130 cements its competence in classification tasks.

LightGBM, another gradient boosting algorithm, displays a precision of 96.102, indicating solid positive prediction accuracy. The recall of 96.632 emphasizes its capacity to capture a substantial portion of actual positive cases. The F1-score of 95.323 signifies its equilibrium between precision and recall, and the accuracy of 97.044 reinforces its accuracy in classification.

The Neural Network, with a precision of 91.843, exhibits a satisfactory ability to predict positive cases. Its recall of 95.501 indicates that it captures a noteworthy number of actual positive instances. The F1-score of 93.931 reflects its trade-off between precision and recall, while the accuracy of 96.424 illustrates its correctness in classifying instances.

Lastly, the Proposed Algorithm, a Multistage 1D CNN, outperforms the others in multiple aspects. Its precision of 99.401 showcases its exceptional accuracy in predicting positive instances. The high recall of 99.213 suggests its remarkable capability to capture almost all actual positive cases. The F1-score of 99.302 harmonizes precision and recall, while the accuracy of 99.142 reinforces its near-perfect correctness in classification.

Gaussian Naive Bayes, despite its simplicity, demonstrates competitive accuracy but lacks in recall, indicating potential false negatives. Logistic Regression proves to be a robust choice with balanced precision and recall, suitable for various applications. Ensemble methods, such as Extra Trees and Random Forest, excel in accuracy and positive prediction precision but may vary in recall due to their inherent randomness. XGBoost and LightGBM stand out with high precision, recall, and accuracy, emphasizing their effectiveness in capturing actual positive cases. Neural Networks offer good recall but may trade off precision, making them suitable for applications where capturing positives is prioritized. The Proposed Algorithm's exceptional performance across all metrics highlights its potential as a powerful classifier for the binary classification task. The results on performance evaluation of the proposed methodology is visually represented in the figure 1.

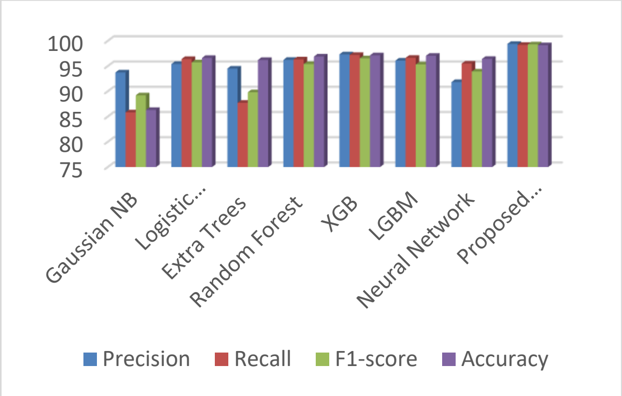

Fig1: Visual Representation of Proposed Model Performance

Conclusion

The study proposed an adaptive 1D CNN model for credit risk prediction task and this proposed methodology is compared with other state of the art models. Among the classical algorithms, Gaussian Naive Bayes demonstrated competitive accuracy, but its limited recall suggests potential shortcomings in capturing all actual positive cases. Logistic Regression emerged as a reliable choice, showcasing a balanced precision-recall trade-off, making it suitable for a wide range of applications. Ensemble methods, such as Extra Trees and Random Forest, exhibited high accuracy and positive prediction precision. However, their recall rates varied due to their inherent randomness. XGBoost and LightGBM stood out with exceptional precision, recall, and accuracy, indicating their effectiveness in identifying true positive cases. Neural Networks, while exhibiting good recall, sometimes traded off precision. They can be a valuable tool in scenarios where capturing positive instances is of higher importance, potentially requiring careful parameter tuning to achieve the desired balance between precision and recall. The spotlight of this study is on the proposed Multistage 1D CNN algorithm, which outperformed all other methods across all evaluation metrics. With exceptional precision, recall, F1-score, and accuracy, the algorithm showcases its potential as a robust classifier for binary classification tasks. The customized weight initialization and the integration of 1D convolutional layers make it highly adaptive to one-dimensional data like tabular data.

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