RMT-NET: REJECT AWARE MULTITASK NETWORK FOR MODELLING MISSING NOT-AT-RANDOM DATA IN FINANCIAL CREDITING SCORE

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ABSTRACT_ Approved or denied loan applications are determined by financial credit rating. Missing-not-at-random selection bias results from the fact that we can only see default/non-default labels for accepted samples while having no observations for rejected samples. Such skewed data makes machine learning algorithms trained on it inherently untrustworthy. Based on both theoretical analysis and real-world data investigation, we find in this work that there is a strong correlation between the rejection/approval classification task and the default/non-default classification task. Consequently, rejection and approval can be useful in teaching default and non-default concepts. As a result, we for the first time suggest using Multi-Task Learning (MTL) to model the biassed credit rating data. In particular, we suggest a brand-new Reject-aware Multi-Task Network (RMT-Net).which, using a gating network based on rejection probability, learns the task weights that regulate the information transfer from the rejection/approval task to the default/non-default task. RMT-Net makes use of the relationship between the two tasks, which states that the default or non-default task must learn more from the rejection/approval task the greater the probability of rejection. Moreover, for modelling scenarios with various rejection/approval techniques, we extend RMT-Net to RMT-Net++. Numerous datasets are used in extensive studies, which provide good evidence of RMT-Net's efficacy on both accepted and rejected samples. Furthermore, RMT-Net++ enhances.

1.INTRODUCTION

CREDIT scoring aims to use machine learning methods to measure customers' default probabilities of credit loans [1] [2] [3] [4] [5] . Based on the evaluated credits, financial institutions such as banks and online lending companies can decide whether to approve or reject credit loan applications.When a customer applies for credit loan, his or her application may be approved or rejected. If the application is approved, it will become an approved sample, and the customer will get the loan. After a period, if the customer repays the credit loan timely, it will be a non-default sample; if the customer fails to timely repay, it will be a default sample. In contrast, if the application is not approved, it will become a rejected sample, and the customer will not get credit loan. Since a rejected sample gets no loans, we have no way to observe whether it will be default or non-default. Above process is illustrated in Fig. 1. Credit scoring models are usually constructed based on approved samples, as we have no ground-truth default/non-default labels for rejected samples [6] [7] [8] [9]. The rejection/approval strategies are usually machine learning models or expert rules based on the features of customers, thus approved and rejected samples share different feature distributions. This makes us face the missing-not-at-random selection bias in data [9] [10] [11]. However, when serving online, credit scoring models need to infer credits of loan applications in feature distributions of both approved and rejected samples. Training models with such biased data has severe consequences that the model parameters are biased [12], i.e., the predicted relation between input features and default probability is incorrect. Using such models on samples across various data distributions leads to significant economic losses [7] [13] [14]. Therefore, for reliable credit scoring, besides the modeling of approved samples, we also need to take rejected ones into consideration and infer their true credits [15].

In practice, machine learning models like Logistic Regression (LR), Support Vector Machines (SVM), Multi-Layer Perceptron (MLP) and XGBoost (XGB) are widely used for modeling credit scoring data. However, they are affected by the missing-not-at-random bias in data to produce reliable and accurate predictions. To tackle this problem, some existing approaches address the selection bias and conduct reject inference from multiple perspectives. Some approaches apply the self-training algorithm [16], which iteratively adds rejected samples with higher default probability as default samples to retrain the model [17]. This is a semisupervised approach [18].

2.LITERATURE SURVEY

Credit scoring is a critical task for financial institutions, and machine learning methods have been increasingly employed to predict default probabilities of credit loans. Traditional methods like Logistic Regression (LR), Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), and XGBoost (XGB) are commonly used in this domain. However, these models often suffer from bias due to missing-not-at-random (MNAR) data, where only the accepted samples have observable outcomes, and rejected samples lack default/non-default labels.

To address MNAR bias, several approaches have been proposed:

1. **Self-Training Algorithms**: Self-training algorithms iteratively classify rejected samples with high default probabilities as defaults and retrain the model. This semi-supervised approach aims to leverage the unlabeled rejected samples to improve the model's performance. Examples include the work by Verstraeten et al. (2015) which applied self-training for reject inference in credit scoring.
2. **Propensity Score Matching**: This method involves estimating the probability of selection (approval) and using it to adjust the sample weights. Techniques like Inverse Probability Weighting (IPW) have been utilized to mitigate selection bias. For instance, Hand and Henley (1997) discussed the application of propensity score methods for credit scoring.
3. **Reject Inference Techniques**: Reject inference techniques attempt to infer the likely outcomes (default/non-default) for rejected applications. Methods such as augmentation, reweighting, and parceling are commonly used. Crook and Banasik (2004) provided a comprehensive review of reject inference methods in credit scoring.
4. **Multi-Task Learning (MTL)**: Multi-task learning involves training a model on multiple related tasks simultaneously. By sharing information across tasks, MTL can improve the performance of each task. Caruana (1997) demonstrated the effectiveness of MTL in various applications, including financial risk assessment.
5. **Deep Learning Approaches**: Recent advancements in deep learning have shown promise in handling MNAR data. Techniques like autoencoders, generative adversarial networks (GANs), and attention mechanisms have been explored. Kingma and Welling (2013) introduced variational autoencoders (VAEs) for handling missing data, which has been adapted for credit scoring.

Despite these advancements, there remains a gap in effectively modeling MNAR data in financial credit scoring using multi-task learning with a reject-aware framework. Our proposed Reject-aware Multi-Task Network (RMT-Net) addresses this gap by incorporating rejection probability into the learning process. RMT-Net leverages the strong correlation between rejection/approval and default/non-default tasks to improve the accuracy and reliability of credit scoring models. Additionally, the extended RMT-Net++ variant adapts to various rejection/approval techniques, further enhancing the model's robustness.

Our extensive studies on multiple datasets demonstrate the efficacy of RMT-Net and RMT-Net++ in handling MNAR data and improving credit scoring performance for both accepted and rejected samples. This novel approach provides a significant advancement in the field of financial credit scoring and offers a practical solution to the challenges posed by MNAR data.

3.PROPOSED SYSTEM

The system that is being suggested utilises a Reject-aware Multi-Task Network (RMT-Net). Based on rejection probability, RMT-Net learns the weights that regulate the information sharing from the rejection/approval task to the default/non-default task via a gating network. Greater information is shared from the rejection/approval network and less trustworthy information can be learned in the default/non-default network with a higher rejection probability. This allows us to customise the information sharing weights in the rejected sample feature distribution and take into account the correlation between the rejected sample and default sample. In addition, we extend RMT-Net to RMT-Net++, which models multiple rejection/approval classification tasks in the MTL framework, and we take into account scenarios with multiple rejection/approval techniques.

3.1 IMPLEMENTAION

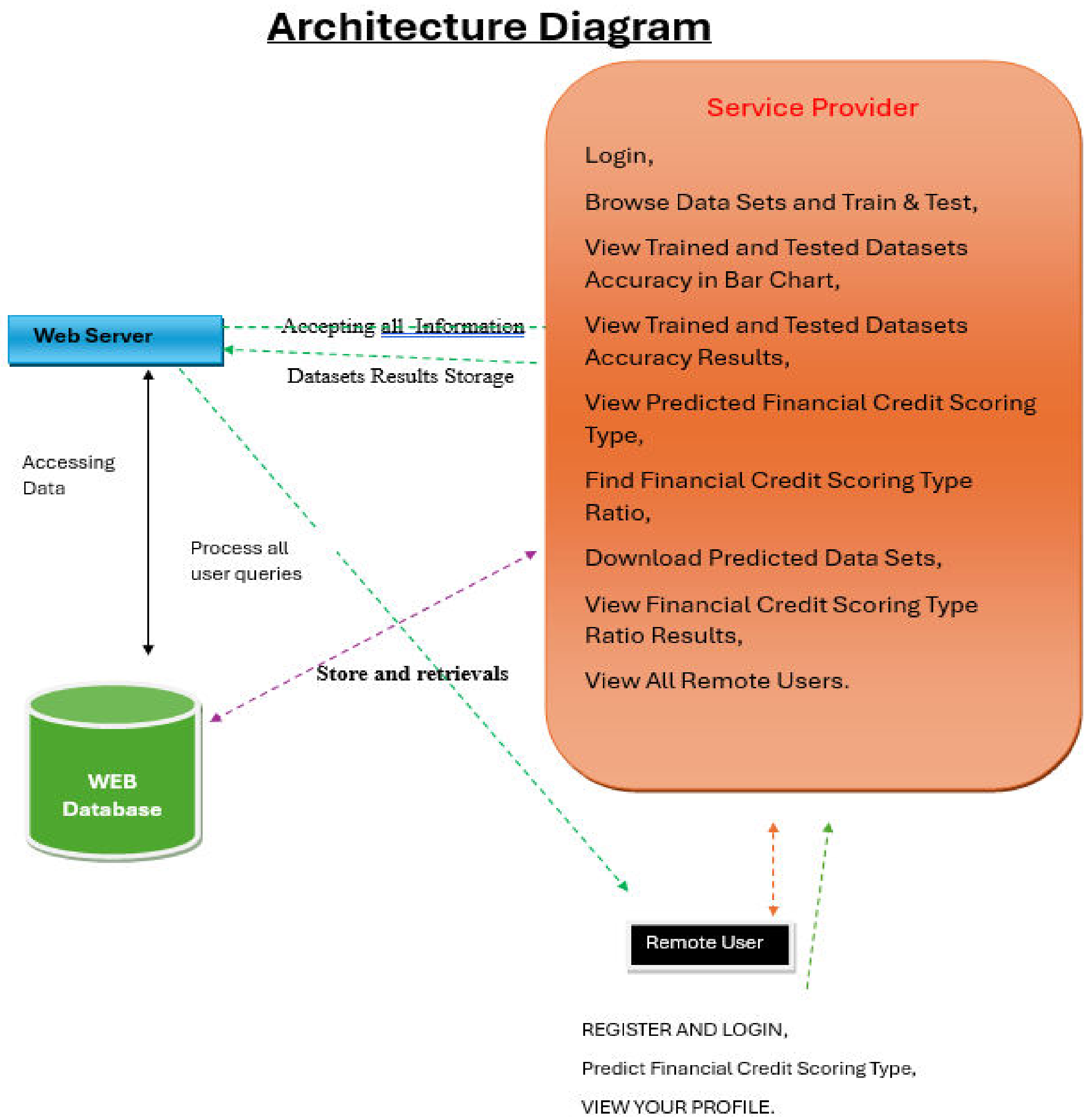

Fig 1:Architecture

4.RESULTS AND DISCUSSION


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RMT Net Reject aware Multi Task Network for Modeling Missing not at random Data in Financial Credit Scoring
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VIEW YOUR PROFILE
LOGOUT
Prediction Of Financial Credit Scoring Type !!!
Enter Data Set Details Here !!!
Enter Customer_Id
Enter Name
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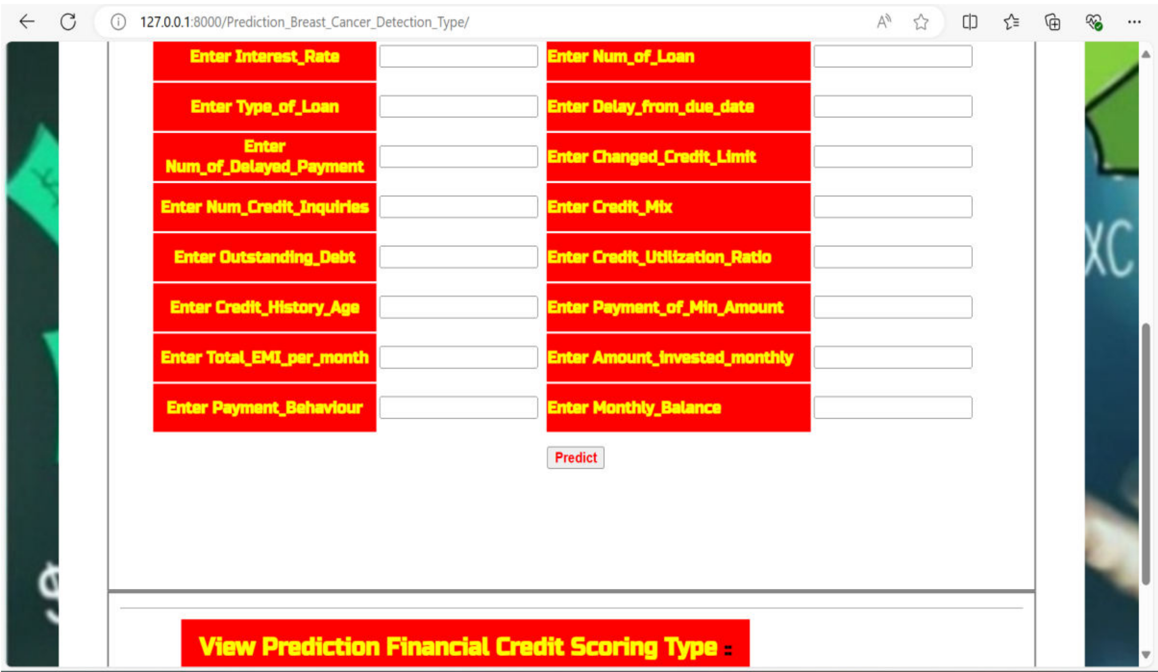
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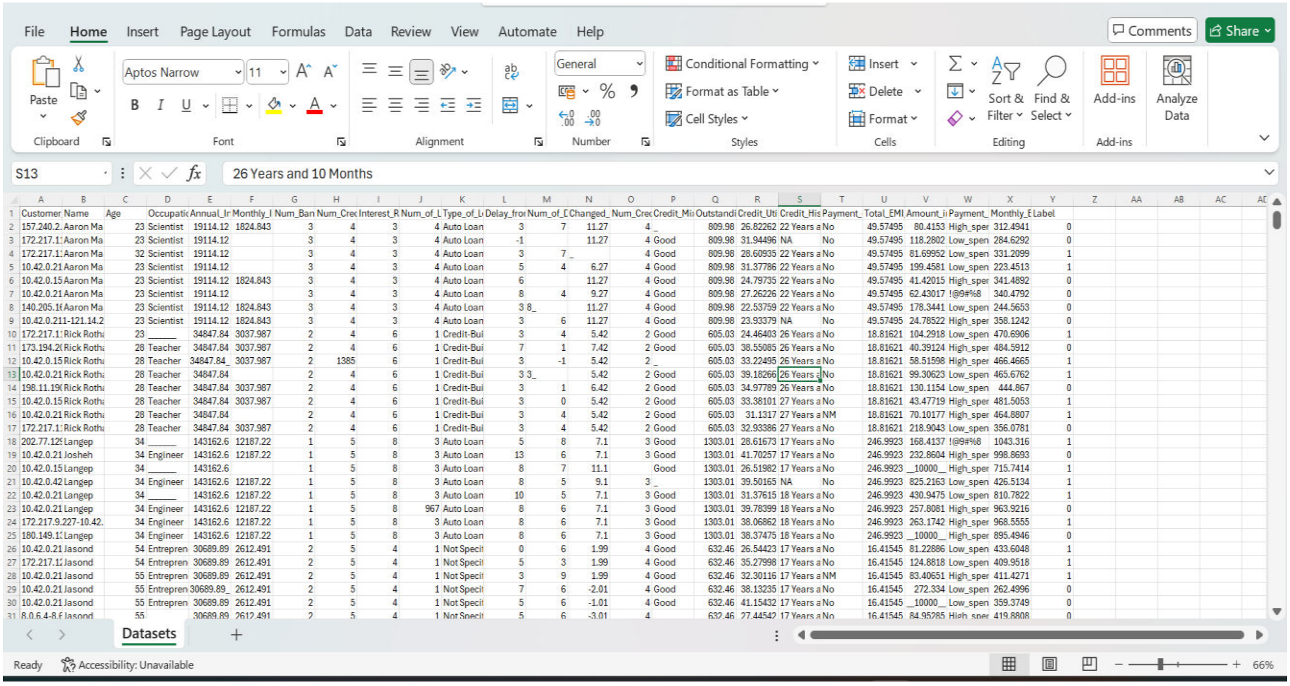
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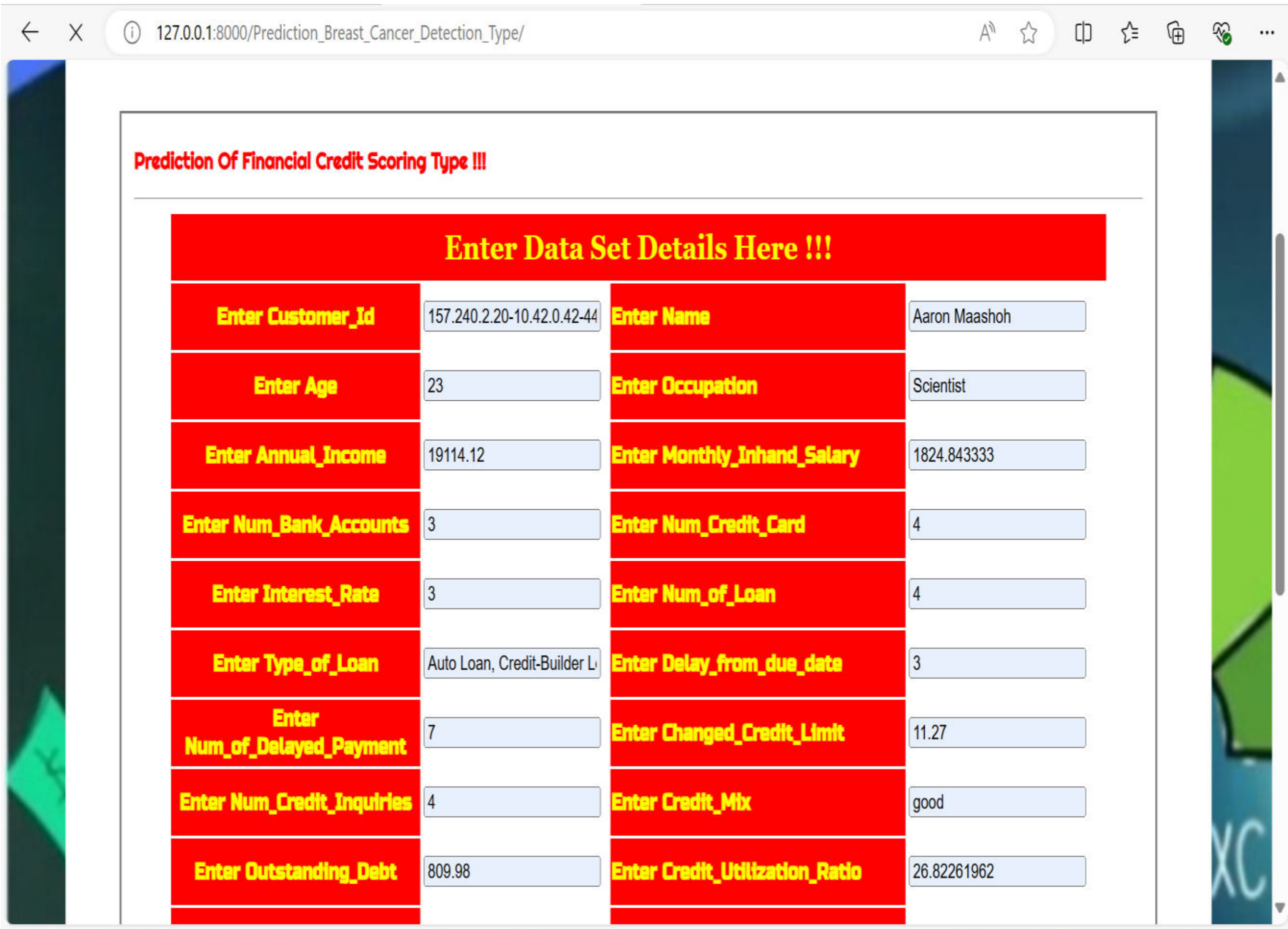
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23
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Scientist
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1824.843333
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3
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3
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7
Enter Changed_Credit_Limit
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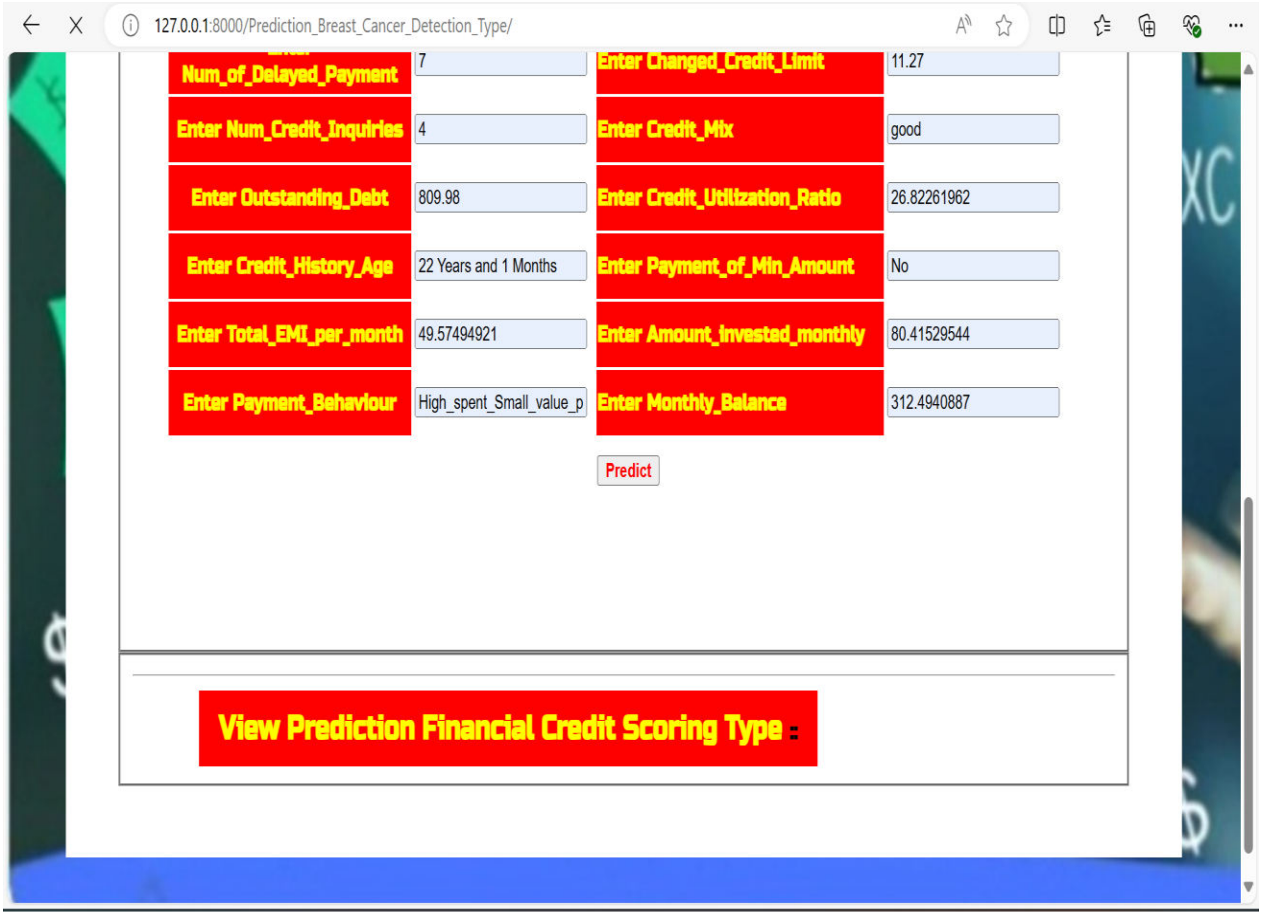

5.CONCLUSION

Modeling biased credit scoring data, in which we only have ground-truth labels for approved samples and no observations for rejected samples, is the primary focus of this paper. We want to improve the accuracy of the prediction on both approved and rejected samples because this bias affects the default prediction's reliability. Based on both theoretical analysis and real-world data, we discover a strong correlation between the rejection/approval classification task and the default/non-default classification task in credit scoring applications. We propose a novel RMT-Net method that uses a gating network based on rejection probabilities to learn the task weights that control the information sharing from the rejection/approval task to the default/non-default task, modeling biased credit scoring data for the first time. RMT Net outperforms a number of cutting-edge methods from a variety of angles in empirical experiments conducted on ten datasets in a variety of settings and significantly improves on the subpar results of existing MTL approaches. Furthermore, we incorporate multiple rejection/approval strategies into our RMT-Net++ extension for scenario modeling. In a further experiment, RMT-Net++'s performance in a more complex multi-policy scenario can be further enhanced by employing multiple strategies.

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