A Deep Learning Approach to Modeling Customer Payment Behavior and Forecasting Receivables: A Company Case Study

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Abstract:

This study analyzes customer payment behavior and develops a deep learning model to predict collection periods and payment methods accurately. Using stock outflow and collection data from the past three years of a Turkish company, a multidimensional dataset was created. The model achieved 88% accuracy, maintaining a 30-day or less difference between actual and predicted durations. This forecasting system optimizes cash flow management, enhances financial processes, and improves credit policies. By surpassing traditional receivables forecasting methods and leveraging advanced data analytics and AI techniques, the study demonstrates deep learning's reliability in predicting receivables and aims to improve financial decision-making.

Keywords: Customer Payment Behavior, Receivables Forecasting, Deep Learning, Credit Management.

1. Introduction

Modeling payment behaviors and forecasting receivables emerge as critical areas that enhance businesses' financial stability and cash flow management capabilities. In an economic environment like Turkey, where commercial practices and payment habits may differ from global norms, analyses in this field offer significant opportunities from both academic and practical perspectives. For instance, pre-determined payment plans are often affected by factors such as economic fluctuations, insufficient demand, or challenges in cash management, leading to extended payment terms and pressure on working capital. Therefore, understanding commercial customers' payment behaviors and forecasting future cash flows not only improves operational efficiency but also enables more effective strategic decision-making.

As highlighted in Daron Acemoglu's book *The Narrow Corridor: States, Societies, and the Fate of Liberty*, the effective functioning of economic and social systems depends on a balanced interaction between states and societies. Acemoglu emphasizes that safeguarding freedoms and fostering economic growth require mutual empowerment of states and individuals within a "narrow corridor"(D. Acemoğlu & Robinson, 2012, 2019). In this context, commercial payment behaviors in Turkey are shaped not only by relationships between individuals and businesses but also by institutional trust, measures taken against economic volatility, and the role of the state. This study examines the unique dynamics of Turkey's commercial environment by leveraging deep learning methods to model payment behaviors and forecast receivables.

The results of the developed model demonstrate that payment durations and methods can be predicted with 88% accuracy, offering valuable contributions to working capital management, credit policies, and budgeting processes. This study provides a crucial step towards better understanding the role of payment habits within the economic system and establishing a foundation for improving models in this area.

In summary, this study aims to model commercial payment behaviors in Turkey using deep learning methods to enhance the reliability of receivables forecasting and deliver actionable insights for working capital management, credit policies, and budgeting processes. Additionally, the study addresses existing gaps in the literature, aiming to improve the understanding of payment behaviors and strengthen forecasting models. The findings are expected to contribute significantly to both academic research and practical business applications.

1.1. Background and motivation

Understanding customer payment behavior is essential for companies, as it directly impacts receivables management and customer risk assessment. Despite its importance, limited research focuses on forecasting receivables payments, with existing studies often restricted to specific industries like mail-order or trucking. Comparisons are typically made between customers who pay promptly and those who delay payments during various stages of the Dunning cycle. Both academics and managers in practice increasingly realize the existence of heterogeneity in payment delays; considerable effort has been made to identify, in addition to some further elements, the likely main determinants. According to research, factors that affect payment behavior are assumed from literature to be: the size of the firm, since they may act as proxies of bankruptcy costs for both wholesalers and retailers; macroeconomic factors like inflation, which reflect the economic environment in which firms operate—they might affect the likelihood that any given firm becomes insolvent; seasonal patterns of customers. Clearly, research indicates that the payment behavior of customers is determined by multiple factors and could change depending on cultural and economic conditions.

In conclusion, modeling the underlying and mostly unobserved payment behavior and forecasting the impact of the explanatory factors on receivables might help cash flow forecasting, working capital management, budgeting, credit granting, and financing. Since receivables forecasting should account for the respective payment behavior or the mix of behavior of various customer categories, modeling diversity was established. It was concluded that in spite of years of economic and managerial experiments into the drivers of payments, there is still not much theoretical and practical explanation of the behavior solely studied here. Based on the research statement above, the payment behavior of some companies, mainly private companies, is explained and predicted using artificial neural networks. Artificial neural networks stand out as an innovative method bridging the gap between theory and real-world data. Inspired by the biological brain's mechanism of perceiving and reacting to information, these models analyze unpredictable and complex customer payment behaviors. The irregular nature of customer decisions leads to a stochastic pattern in payments, making receivables forecasting more challenging. Neural networks help make sense of this randomness, enabling more accurate predictions (Nimmagadda, 2022). Additionally, managers believe that effectively leveraging the vast corporate memory accumulated over the years can lead to even more accurate forecasts in the future

1.2. Research Objectives

The primary objective of this study is to conduct an in-depth analysis of customer payment behavior and develop a deep learning-based financial model that effectively incorporates all relevant variables while addressing diverse customer characteristics and risk groups. The research aims to examine the complex factors influencing customer payment behavior within the context of a specific company and to present an advanced model that delivers highly accurate receivables forecasting. Through detailed analysis and synthesis of various datasets, the study seeks to achieve a better understanding of the

2. Literature Review

Progress in understanding customer payment behavior can be traced back to several different fields—from accounting theories to neoclassical economics. Different theoretical approaches have contributed to the increasingly sophisticated understanding of customer payment behavior. Accounting theories, institutional, and transaction cost economics theories in the related literature favorably looked at psychology and social context. Some scholars also blamed the creditworthiness evaluation process itself for promoting behavior in debtors to delay payment. Indeed, among competing theories, the contractual and legal views have the most dominant position in the literature, indicating who bears the highest collection cost and who has effective collection mechanisms. Some empirical studies provided enhanced qualitative insights into predictive customer payment behavior. Companies in different industries construct a variety of models using multiple methodologies to predict customer payment behavior. Historically, the literature on modeling customer payment behavior is sparse, and this study is a valuable cohort identified based on the systematic iterative review. It is clear that further research on the subject is variable, particularly in respect to the need for relevant predictors of payment behavior within the B2B area, and it is clear that one of the foci of future research should be identifying and locating new large-volume data repositories so as to engage in the development of much larger prediction models. Companies have employed different forecasting methods in the context of receivables management. The latest techniques we have seen applied to the prediction of days sales Outstanding as a proxy for predicting short-term cash flows are those that belong to the class of AI. The literature on AI techniques has shown better performance metrics and results when compared to traditional methodologies. However, the context in applying these AI techniques is often only in this field, given its novelty. Therefore, it has been indicated that a more critical and cautious assessment is needed in predicting due to the limited understanding of the reasons for payment delays beyond the variables used within the predictive models. This research aims to make a fundamental contribution to the literature by examining long-term company data to provide a comprehensive analysis of the predictability of the receivables system using deep learning methods.

The use of machine learning (ML) and deep learning (DL) in predicting accounts receivables and customer payment behaviors has gained traction in various sectors. Kim and Kang's (Kim & Kang, 2016)study introduces machine learning models aimed at optimizing call center agent allocation based on the likelihood of customer payments. They highlight that traditional heuristic-based methods lack the adaptability of ML algorithms, which provide more accurate predictions through models like decision trees, neural networks, and support vector machines. Their results demonstrate that ML-based scoring rules significantly improve prediction accuracy and agent performance by efficiently focusing on high-priority customers.

Recent research by Moore and Vuuren (Moore & van Vuuren, 2024) addresses the challenges businesses face with late payments, which can hinder cash flow management. Their framework integrates survival analysis with machine learning to predict customer payment behaviors and streamline the invoice-to-cash process. They propose a "survival boost" approach that combines the benefits of survival analysis and machine learning to enhance prediction accuracy. This approach demonstrates a significant improvement in predicting late payments compared to models based solely on survival analysis, or ML, underscoring the value of ensemble methods in accounts receivable contexts.

Bahrami et al. (Bahrami et al., 2020) explore behavioral analytics for invoice payment prediction, focusing on the effectiveness of logistic regression and support vector machines (SVMs). Their study highlights the critical role of customer behavior, especially their responses to collection actions, as a pivotal predictor of future payment behavior. By analyzing over 1.6 million customer records, they achieve a prediction accuracy of up to 97%, demonstrating the model's effectiveness in guiding collection strategies and reducing the need for corporate lines of credit.

Kureljusic and Metz (Kureljusic & Metz, 2023) analyze various ML algorithms for predicting customer payment dates and assess their applicability in accounts receivable management. Their findings demonstrate that neural networks excel over other methods in terms of prediction accuracy. They argue that accurate forecasting enables firms to proactively manage cash flows, reducing reliance on reactive measures like loan applications. Their study also suggests that ML methods allow businesses to transition from monthly to daily forecasting, aligning with real-time financial management practices.

Appel et al. (Appel et al., 2020) present a case study on leveraging ML for account receivables prediction, specifically in a multinational banking context. They emphasize that customer payment behavior is not always systematically recorded, complicating prediction efforts. Despite these challenges, their prototype achieves an 81% prediction accuracy, significantly enhancing the efficiency of collectors by prioritizing high-risk accounts. The study illustrates the substantial financial impact of using ML for prioritization, reporting savings of up to $1.75 million monthly.

Tuovinen's (Tuovinen, 2020) study explores the implementation of real-time data in forecasting financial risk and credit ratings for SMEs. His research discovers that integrating real-time data into credit rating processes enhances the accuracy of financial risk assessments. By leveraging logistic regression models, his findings suggest that payment behavior significantly impacts credit ratings, providing businesses with a more dynamic tool for assessing client risk profiles. Tuovinen’s work highlights the evolving role of accounting data in real-time credit evaluations.

Stahl (Stahl, 2018) examines the importance of selecting appropriate models for forecasting human behavior in financial decision-making. He emphasizes the issue of overfitting in predictive models, where more complex models do not necessarily yield better out-of-sample predictions. His study on rank-dependent expected utility versus expected utility models in behavioral economics underscores the necessity of balancing model complexity with predictive reliability. Stahl’s findings are particularly relevant for forecasting models in accounts receivable management, where model simplicity can sometimes outperform more complex alternatives in predictive tasks.

This literature collectively demonstrates that ML and DL techniques provide significant advantages in forecasting payment behaviors, credit risks, and accounts receivable management. Integrating real-time data and behavioral analytics significantly boosts the predictive accuracy of these models, facilitating firms' transition to proactive and precise cash flow management practices.

2.1. Customer Payment Behavior Modeling

A number of models have been developed to analyze customer payment behavior. These models use theoretical assumptions about human behavior, the analysis of data on the payment behavior of a particular group of customers, or on the basis of the behavior of this or a similar group of economic operators. This group of models also deals with what customers actually do. It should be noted that many of these models can also be used in modeling distress behavior. Real-world payment systems and therefore empirical payment data must be used to do business. There are a number of factors that influence the payment behavior of customers, including company policies, financial constraints, rights from both parties, and the economic health of the country from which the customer originates. There are certainly several factors within your organization that influence this behavior, such as the terms and wording of the credit agreements, a unique pricing strategy for selected customers, the way your collection department operates, and the criteria used based on which customers are accepted or declined credit. The factors that are important to successful companies in this area are both regular and economic dimensions. They can be traced back to pragmatic definitions of the liquidity information of an intermediary balance sheet.

For some time, companies can use customer payment data to analyze the lives of their customers. Following these analyses, models were used to create data models, the results of which are used in operational use. Companies use these models for credit management and collection. Traditional methods were slightly worse, and newer machine/deep learning and predictive analysis methods seemed to have contrasting results, with the conclusions of one study being more successful than another. Little more than a dozen studies have been conducted that predict the payment system needed for the most economically ambitious company to use something practical. The purpose of models to predict payment behavior is to divide all the demand for a company into segments of different types of time: delayed, little, or no possible payment. Such prediction models can be improved and made more precise in each segment. It is important to conduct this verification, as any improvement in manual predictions that will return volatile results will require certain costs that companies must bear. This is especially important in the current volatile world where forecasts are usually made directly to technology, which can support and serve accurate predictions for various parameters.

2.2. Receivables Forecasting Techniques

Several techniques are employed in various organizations for forecasting their receivables. These receivables forecasting techniques can be further classified into qualitative forecasting techniques and quantitative approaches. Each approach has its own merits and scope. Traditional statistical techniques such as time series analysis and naive methods are used for forecasting. The use of advanced analytics methods by IT-enabled systems, such as artificial intelligence, is still in an emerging stage. This will not only help in automatically predicting the receivables registered as provision but also assist in real-time analytics for managing the liquidity of the firm. The qualitative forecasting technique involves predicting future expected cash inflow based upon specific circumstances rather than implementing a strategy or utilizing a computer model. One of the factors affecting the accurate prediction of receivables is that it may not capture the potential for misstatement in the allowance for doubtful accounts due to management bias.

Irrespective of the forecasting technique used, forecasting is subject to various uncertainties owing to factors such as the inaccuracy of prior data, process timing, and the economic scenario of the business. The following are the factors of importance in the development of good forecasting techniques for the receivables of a firm: organization size, type of industry, nature of purchases, market areas, types of customers, extensions of credit, and number of customers. A few trends will impact the area of forecasting more or less. With the increasing penetration of technology in every field, radically innovative trends in analytics are on the horizon. In the future, with better and more data-driven inputs, the forecast would be accurate to a level where different possibilities could be ranked based on the analyzed predictions. Such forecasts can throw light on the realm of dark opportunities and can lead to an innovative strategy for generating income for the organization.

2. Methodology

This study adopts a hybrid methodological approach that combines classical statistical methods with artificial intelligence techniques to address the need for predicting customer payment behavior. The research process began with case-based interviews aimed at understanding the unique dynamics of the company's forecasting process, and these findings were further supported by advanced data analytics to develop a customized deep learning-based prediction model. This approach not only seeks to comprehend the company's operational needs but also aims to provide valuable insights that facilitate strategic decision-making in cash flow forecasting and receivables management.

3.1. Data Collection

DXXX Machinery Trade Co. Ltd.maintains records of over 100,000 client companies. Each client has transactional records in the VEGA and LOGO systems. In this study, the focus of analysis was on transactional records, which were categorized into two main groups. First, the date and amount of purchases made by client companies from DXXX Machinery Trade Co. Ltd. were analyzed. Within this scope, the database provided the dates and amounts of each sales transaction, recorded as inventory outflow. Second, the dates and amounts of collections made from client companies were evaluated. A critical distinction between these two types of data is that inventory outflows and collection records are independent of one another. In other words, client companies often make payments for purchased products at later dates, sometimes covering multiple past purchases either in full or in installments. Consequently, the company records collections in its ERP system without associating them directly with specific inventory outflows.

To associate collection records with inventory outflows, the FIFO (First-In-First-Out) method was applied, whereby payments from clients were matched starting with the oldest inventory outflows. At DXXX Machinery Trade Co. Ltd., collections are made through four different methods: cash, check, bank transfer, and credit card. Based on this data, various calculations were performed to prepare data inputs suitable for a deep learning model by distributing the collections to inventory outflows using the FIFO method. To facilitate better understanding of these calculations, a step-by-step example is provided below using Client X. Summary tables containing the inventory outflows and collections for Client X are presented in Tables 1 and 2.

Table 1. Inventory Outflow Records for Client X

Company	Inventory Outflow Record No	Inventory Outflow Amount	Inventory Outflow Date
X	A0001	100	1.01.2023
X	A0002	200	21.03.2023

Table 2. Collection Entry Records for Client X

Company	Collection Record No	Collection Method	Collection Amount	Collection Date
X	B0001	Check	60	1.03.2023
X	B0002	Bank Transfer	40	21.05.2023
X	B0003	Bank Transfer	50	21.08.2023
X	B0004	Check	80	30.08.2023
X	B0005	Bank Transfer	20	10.09.2023
X	B0006	Cash	50	30.09.2023

First, as shown in Table 3, collections received from client companies were matched with inventory outflow records using the FIFO method. As a result of these matchings, the collection period between the inventory outflow date and the collection date was calculated. In Table 3, the data labeled as "Inventory Outflow Amount" is defined as the G0 input for the deep learning model to be developed.

Table 3. Collection Records Allocated to Inventory Outflow Records Using the FIFO Method

Company	Inventory Outflow Record No	Inventory Outflow Amount (G0)	Inventory Outflow Date	Collection Record No	Collection Method	Collection Amount	Collection Date	Collection Period
X	A0001	100	1.01.2023	B0001	Check	60	1.03.2023	59

X	A0001	100	1.01.2023	B0002	Bank Transfer	40	21.05.2023	140
X	A0002	200	21.03.2023	B0003	Bank Transfer	50	21.08.2023	153
X	A0002	200	21.03.2023	B0004	Check	80	30.08.2023	162
X	A0002	200	21.03.2023	B0005	Bank Transfer	20	10.09.2023	173
X	A0002	200	21.03.2023	B0006	Cash	50	30.09.2023	193

The second inputs for the deep learning model (G1-1, G1-2, G1-3, G1-4) present a detailed distribution of the total collections made by the respective client company up to each inventory outflow record date, categorized by collection methods (Cash, Check, Bank Transfer, Credit Card). These details are elaborated in Table 4. This distribution demonstrates, on a per inventory outflow record basis, the proportions of collection methods used by the client company based on their past collections. In the last row of Table 4, an example calculation is provided to illustrate the methodology used for these computations.

Table 4. Cumulative Collection Method Usage Ratios Up to the Relevant Inventory Outflow Date

Inventory Outflow Record No	Collection Record No	Collection Method	Collection Amount	Cumulative Collection Amount	Bank Transfer Usage Ratio (G1-1)	Cash Usage Ratio (G1-2)	Credit Usage Ratio (G1-3)	Check Usage Ratio (G1-4)
A0001	B0001	Check	60	60	0.00	0.00	0.00	1.00
A0001	B0002	Bank Transfer	40	100	0.40	0.00	0.00	0.60
A0002	B0003	Bank Transfer	50	150	0.60	0.00	0.00	0.40
A0002	B0004	Check	80	230	0.39	0.00	0.00	0.61
A0002	B0005	Bank Transfer	20	250	0.44	0.00	0.00	0.56
A0002	B0006	Cash	50	300	0.37*	0.17*	0.00*	0.47*

*Bank Transfer Usage Ratio (G1-1) 0.37=((40+50+20)/300)
*Cash Usage Ratio (G1-2) 0.17 =(50/300)
*Credit Usage Ratio (G1-3) 0.00=(0/300)
*Check Usage Ratio (G1-4) 0.47=((60+80)/300)

The third inputs for the deep learning model (G2-1, G2-2, G2-3, G2-4) provide information on the average time taken by the respective client to complete collections up to a specific inventory outflow record date, regardless of the collection method. The average collection periods have been calculated using a weighted approach based on collection amounts, and the results are presented in Table 5. In the second row of Table 5, a sample calculation is provided to illustrate the computation process.

Table 5. Average Collection Period up to Each Inventory Outflow Date

Inventory Outflow Record No	Collection Record No	Collection Method	Collection Amount	Collection Date	Collection Period	Weighted Average Collection Period(G2)
A0001	B0001	Check	60	1.03.2023	59	59
A0001	B0002	Bank Transfer	40	21.05.2023	140	91 *
A0002	B0003	Bank Transfer	50	21.08.2023	153	112

A0002	B0004	Check	80	30.08.2023	162	129
A0002	B0005	Bank Transfer	20	10.09.2023	173	133
A0002	B0006	Cash	50	30.09.2023	193	143

*Weighted Average Collection Period(G2) 91= (60*59+40*140)/(60+40)

The fourth inputs for the deep learning model (G3-1, G3-2, G3-3, G3-4) provide information on the average time taken by the respective client to complete collections for each collection method up to a specific inventory outflow record date. The average collection periods have been calculated using a weighted approach based on collection amounts, and the results are presented in Table 6. In the third row of Table 6, a sample calculation is provided to illustrate the computation process.

Table 6. Average Collection Period by Collection Method up to Each Inventory Outflow Date

Inventory Outflow Record No	Collection Record No	Collection Method	Collection Amount	Collection Period	Collection Period for Bank Transfer (G3-1)	Collection Period for Cash (G3-2)	Collection Period for Credit (G3-3)	Collection Period for Check (G3-4)
A0001	B0001	Check	60	59				59
A0001	B0002	Bank Transfer	40	140	140			59
A0002	B0003	Bank Transfer	50	153	147*			59*
A0002	B0004	Check	80	162	147			118
A0002	B0005	Bank Transfer	20	173	152			118
A0002	B0006	Cash	50	193	152	193		118

*Collection Period for Bank Transfer (G3-1) 147=(50*153+40*140)/(40+50)
*Collection Period for Check (G3-4) 59=(60*59)/60

In this study, using the G0, G1, G2, and G3 inputs, the aim is to predict the date and the collection method for the payment associated with a customer's inventory outflow record. The model seeks to forecast the timing and method of future collections by analyzing the customer's past collection habits. Therefore, as shown in Table 7, the collection ratios for each inventory record within the categories of Check, Cash, Advance Payment, and Bank Transfer were calculated for training the data. These target parameters are referred to within the study as H0-1, H0-2, H0-3, and H0-4, respectively.

Table 7. Collection Method Usage Ratios by Inventory Outflow Record

Inventory Outflow Record No	Collection Record No	Bank Transfer Usage Ratio (H0-1)	Cash Usage Ratio (H0-2)	Credit Usage Ratio (H0-3)	Check Usage Ratio (H0-4)
A0001	B0001 , B0002	0.4 (40/100)	0	0	0.6 (60/100)
A0002	B0003, B0004, B0005, B0006	0.35 (70/200)	0.25 (50/200)	0	0.4 (80/200)

As shown in Table 8, the collection period for an inventory outflow record has been calculated by considering the probabilities of collections being made on different dates and through various methods. This calculation was performed by creating a weighted average of the collection periods associated with an inventory outflow record, where the weights are based on the collection amounts. Thus, the overall impact of the collection periods has been summarized into a single representative value, which is referred to as H1 in this study.

Table 8. Weighted Average Collection Period by Inventory Outflow Record

Inventory Outflow Record No	Collection Record No	Weighted Average Collection Period (H1)
A0001	B0001 , B0002	91 (60*59+40*140)/100
A0002	B0003, B0004, B0005, B0006	169 (50*153+80*162+20*173+50*193)/200

In summary, all calculations and processes related to the G0, G1, G2, G3, H0, and H1 codes for use in the deep learning model were automatically performed in Python on data from 47,456 client companies with transaction records from the past three years. As a result of this process, a comprehensive dataset consisting of 89,133 rows was prepared. During prediction using deep learning, inputs such as G1-1, G1-2, G1-3, G1-4, G2, G3-1, G3-2, G3-3, and G3-4 were not yet known for the current inventory outflow record. Therefore, a shifting process was applied to the dataset, ensuring that records from the previous inventory outflow of the respective client were considered. The dataset was organized accordingly. Additionally, 4,993 inventory outflow records could not be matched with collections due to insufficient payments. Non-credit, cash-based inventory outflows were excluded from the dataset.

3.2. Model Development

In this study, a deep learning model was developed to capture the complex dynamics of client collection behaviors using structured financial data provided by DXXX Machinery Trade Co. Ltd. As shown in Figure 1, the model architecture was carefully designed with a combination of dense layers that progressively extract low-level and high-level features. The input layer accepts a vector consisting of 13 features, including cumulative collection ratios, weighted average collection periods, and distributions related to collection methods. These inputs are passed to the first dense layer with 128 neurons, where low-level feature extraction is performed. Subsequently, the second dense layer, with 256 neurons, extracts more abstract and high-level features.

The concatenation layer combines the outputs of both dense layers, enabling the model to conduct an integrated analysis of detailed and abstract features. Next, the model's third dense layer processes the merged 384-dimensional inputs within a structure of 128 neurons, optimizing high-level features to improve prediction accuracy. To prevent overfitting and enhance the generalization capability of the model, a dropout layer is added after this dense layer. Finally, the output layer comprises six neurons, enabling the model to accurately predict the usage ratios of different collection methods and collection periods.

The performance of the model was evaluated by dividing the dataset, which consists of 89,133 rows corresponding to 47,456 clients, into 80% for training and 20% for testing.

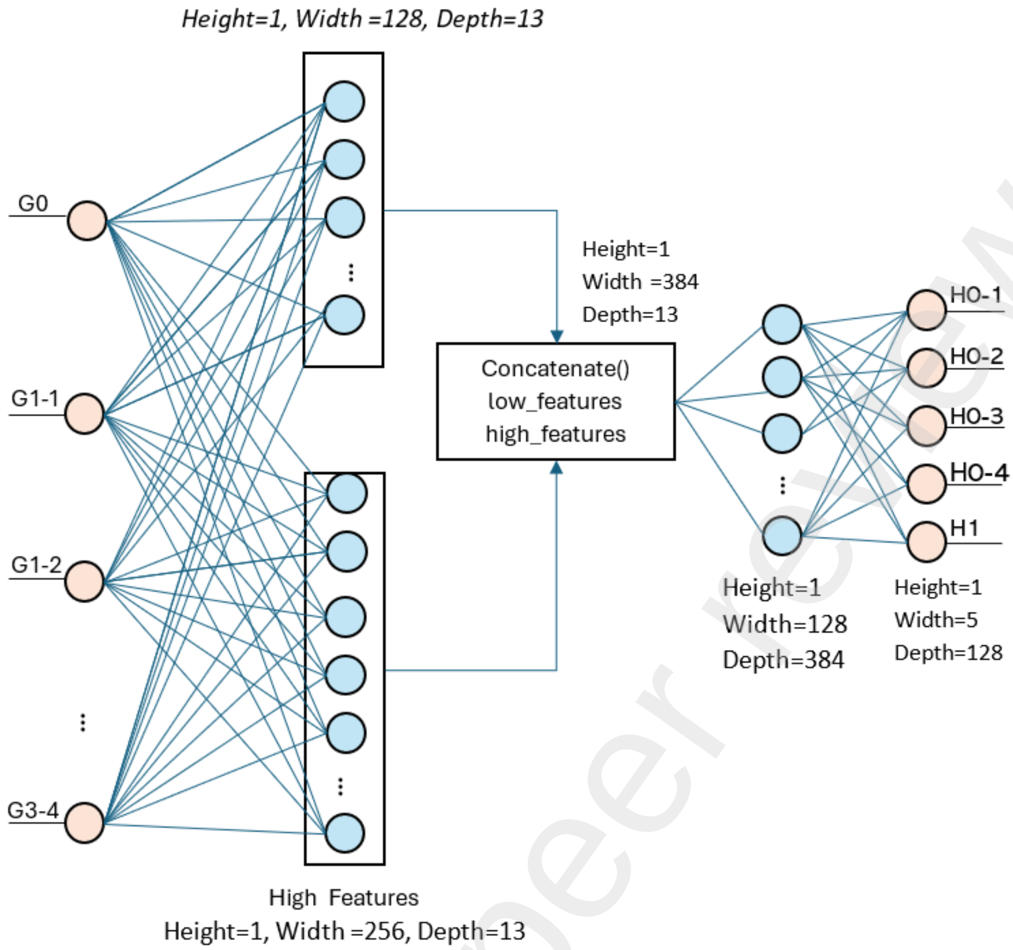

Figure 1. Deep Learning Model

In this study, various deep learning models with different layer architectures, such as GRU and LSTM, were tested. Performance evaluation revealed that some of these models produced results within 1-5% of the proposed model's performance, either higher or lower. This outcome was expected, as the preprocessing stage established meaningful structural connections between temporal data, historical insights, and inventory outflow records. This process contributed to achieving similar performance levels. This finding highlights the significant impact of the data preprocessing and structuring phase on the model's success.

Among the tested deep learning models, only the results of the model that demonstrated the highest performance during the testing phase were included in the study. This decision was made to strengthen the study's focus and avoid unnecessarily expanding the scope of the text. This approach allowed the analysis to concentrate on the model that provided the best results, rather than delving into detailed comparisons of other models' performances.

4. Results and Analysis

The data used in the deep learning model was analyzed using descriptive statistical methods to examine its fundamental characteristics and provide a strong foundation for the modeling process. In Figure 2, the frequency distribution of inventory outflow amounts across different ranges is displayed. It is observed that the most frequent transaction range is "0-500," accounting for 47972 transactions, indicating the dominance of small-value transactions. As the value ranges increase, a significant decrease in transaction frequency is observed, with transactions becoming particularly sparse in the

"5001-10000" range and beyond. However, the occurrence of transactions in the "500000+" category indicates that large-value transactions also continue with a certain regularity.

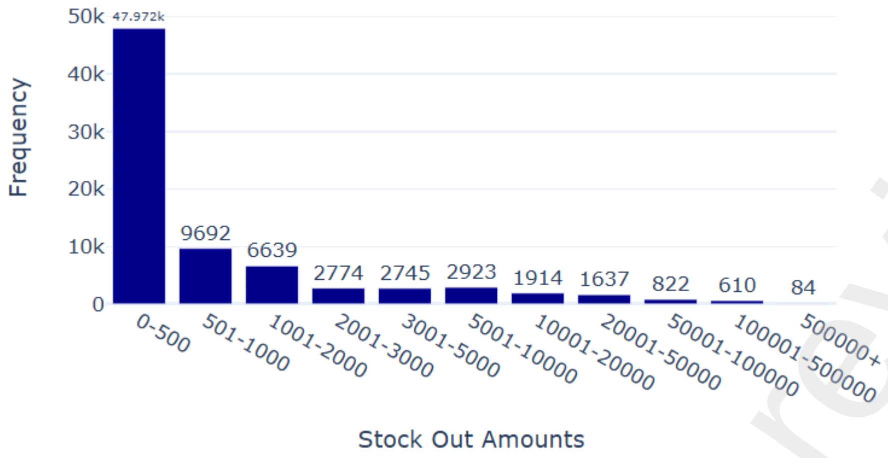

Figure 2. Distribution of Inventory Outflow Amounts

Figure 3 illustrates the usage ratios of different payment methods, showing that the highest usage ratio is 40% for "Bank Transfer." In contrast, the "Cash" method has the lowest usage ratio at 2%, while the other methods exhibit a more balanced distribution. The low usage of the Cash method is an expected outcome, as non-credit, cash-based inventory outflows were excluded from the dataset.

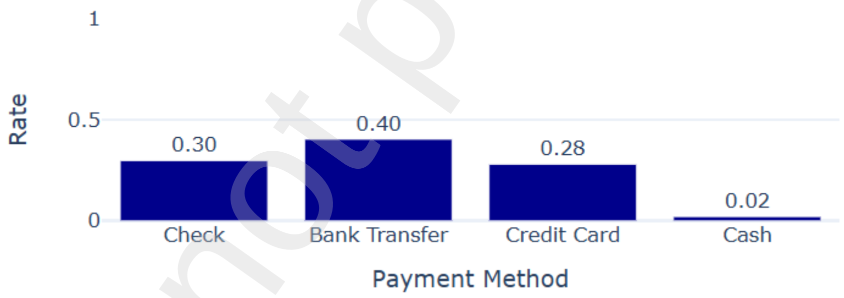

Figure 3. Distribution of Payment Methods

The Figure 4 illustrates the frequency of payment durations across different categories, providing valuable insights into businesses' collection behaviors. The most common payment durations are concentrated in the 60-120 days (33,647 transactions) and 30-60 days (26,327 transactions) ranges, indicating a clear tendency toward medium-term collection periods. The lower frequency of shorter (0-10 days) and longer (over 180 days) payment durations suggests that both quick collections and delayed collections are rare, highlighting opportunities for businesses to optimize their collection processes.

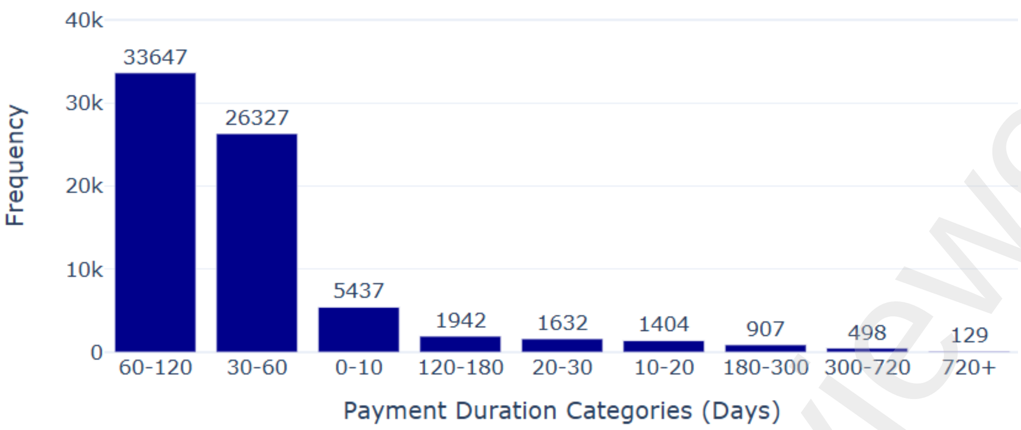

Figure 4. Distribution of Payment Periods

In this study, the developed model predicted how long it would take for collections related to the inventory outflow records of DXXX Machinery Trade Co. Ltd. over the past three years to be completed and the ratios at which different collection methods were preferred. To evaluate the model's prediction performance, the absolute difference/deviation between the actual collection period and the model-predicted collection period was calculated. These deviations were visualized as a histogram based on the frequency of inventory outflow records and are presented in Figure 5. As shown in Figure 5, the deviations are predominantly within 25 days or less.

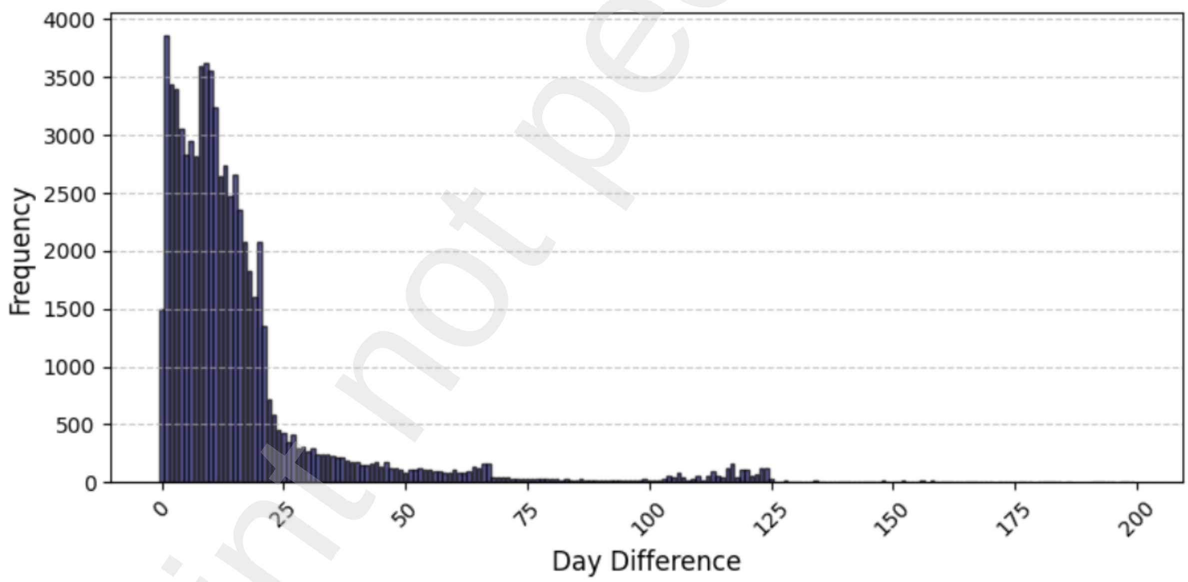

Figure 5. Analysis of Deviations in Collection Periods Based on Inventory Outflow Frequency

Similarly, these deviations were visualized as a histogram based on the frequency of inventory outflow amounts and are presented in Figure 6. In Figure 6, it can be observed that a significant portion of the total debt amounts is concentrated within the 0-25 day deviation range. Moreover, as the delay period increases (e.g., 25 days and above), there is a noticeable decline in the share of the debt amounts. This indicates that the model can accurately predict a substantial portion of the total debt amounts within a time frame that allows the company to effectively manage its cash flow.

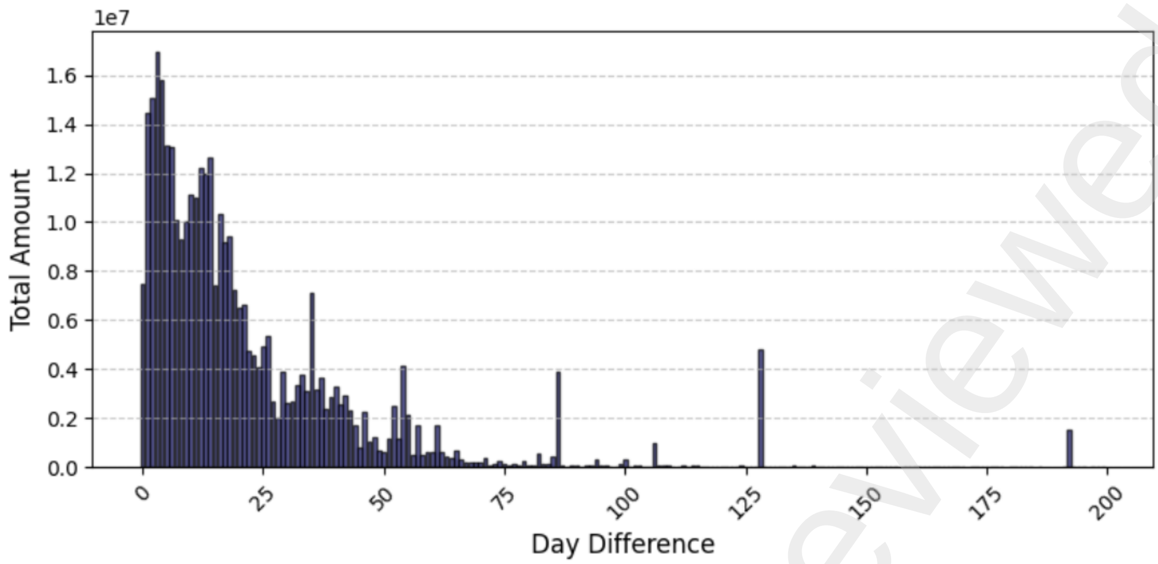

Figure 6. Analysis of Deviations in Collection Periods Based on Inventory Outflow Amount Frequency

To present the results in a more concise manner, the collection period, initially a continuous variable, was transformed into a categorical variable. In this transformation, the absolute value of the difference between the actual collection period and the model-predicted collection period was used. If the difference was between 0-10 days, it was classified as 'Class 1'; if between 10-20 days, it was classified as 'Class 2'; and if exceeding 90 days, it was defined as 'Out of Range.' The prediction performance of the deep learning model based on this class structure is summarized in Table 9.

Table 9. Prediction Performance of the Deep Learning Model

Class	**Absolute Day Difference Between Predicted and Actual Collection Dates**	**Number of Inventory Outflow Records**	**Debt Amount Percentage**	**Debt Amount Percentage (Cumulative)**	**Percentage of Inventory Outflow Records**	**Percentage of Inventory Outflow Records (Cumulative)**
1	0-10 days	32866	0.36	0.36	0.46	0.46
2	11-20 days	24459	0.28	0.64	0.34	0.80
3	21-30 days	5991	0.12	0.75	0.08	0.88
4	31-40 days	2254	0.10	0.85	0.03	0.91
5	41-50 days	1415	0.05	0.90	0.02	0.93
6	51-60 days	998	0.04	0.94	0.01	0.95
7	61-70 days	969	0.01	0.95	0.01	0.96
8	71-80 days	283	0.00	0.96	0.00	0.96
9	81-90 days	225	0.01	0.97	0.00	0.97
Out of range	90+ days	2462	0.03	1.00	0.03	1.00

A total of 71,922 inventory outflow records were analyzed, and for 46% of them, the deviation between the actual collection time and the predicted collection time was between 0-10 days. This success rate corresponds to 36% of the total inventory outflow amounts for the predicted records. Additionally, when examining deviations in collection times within 0-30 days, 88% of the inventory outflow records and 75% of the total outflow amounts had a deviation of less than 30 days. When examining collection time deviations within the 0-40 day range, 91% of the records and 85% of the total amounts fall within this range. This indicates that the model accurately predicts collection periods for the majority of records and that collections are made within at most 30 days of the predicted time frame.

The 3% of records classified under the "Out of Range" category represent large deviations between the predicted and actual collection periods. From a financial management perspective, this could pose a minor risk factor. Such deviations may lead to delays in collection processes or imbalances in cash flow. Nevertheless, the low proportion of this category demonstrates that the model performs well for the majority of records and that the predictions are valid for most cases. These insights are crucial for debt management and cash flow optimization, enabling the company to better plan its collection processes and efficiently manage working capital.

Table 10 presents the distribution of differences between predicted and actual collection periods by payment method. It was observed that for inventory outflow records correctly predicted within the 0-20 days range, collections were made collectively and with approximately equal weight among the Check, Bank Transfer, and Credit payment methods. However, deviations of 80 days or more were predominantly associated with collections made via Bank Transfer, accounting for 60%-90% of such cases. This finding suggests that the model struggles to accurately predict the collection behavior of clients using Bank Transfer or that the behavior of clients making payments via Bank Transfer is inherently unpredictable and irregular. Consequently, these results highlight the need for improvements in the model's Bank Transfer-based collection predictions or a more in-depth analysis of the inconsistencies in the behavior of clients using this payment method.

Table 10. Distribution Percentages of Collection Methods by Deviation Class Structure

Deviation Class	Check	Bank Transfer	Credit Card	Cash
1	0.302	0.368	0.316	0.014
2	0.286	0.394	0.31	0.01
3	0.311	0.433	0.239	0.017
4	0.303	0.444	0.231	0.023
5	0.302	0.459	0.189	0.05
6	0.474	0.348	0.149	0.029
7	0.281	0.291	0.382	0.046
8	0.185	0.609	0.197	0.009
9	0.026	0.914	0.053	0.007
Out of range	0.261	0.619	0.113	0.008

The model's prediction accuracy was also analyzed for three specific clients that the company is particularly interested in, and the results are summarized in Table 11. For the first client (Company X), an evaluation based on the criteria of a maximum 30-day delay showed that out of a total of 113 inventory outflow transactions, 85 were accurately predicted, representing 80% of the total collection amount. For Company Y, the same analysis showed that out of 96 inventory outflow transactions, 65 were correctly predicted, reflecting 78% of the total collection amount. For Company Z, 30 out of 40 inventory outflow transactions were correctly predicted, representing 76% of the total collection amount. These results demonstrate that the model exhibits varying levels of success in collection predictions on a company-by-company basis.

Table 11. Performance of the Deep Learning Model – 3 Company Examples

Company Name	Deviation Class	Total Dept	Amount of Inventory Outflow	Rate
Company X	1	39	2,099,923.73	0.3
Company X	2	24	2,349,512.86	0.63
Company X	3	22	1,164,753.37	0.8
Company X	4	11	658,686.30	0.89
Company X	5	11	324,753.95	0.94
Company X	6	3	306,232.98	0.98
Company X	7	1	15,172.50	0.98
Company X	8	1	109,530.94	1
Company X	9	1	6,031.52	1
Company Y	1	26	487,237.43	0.27
Company Y	2	18	504,492.96	0.55
Company Y	3	21	407,095.25	0.78
Company Y	4	15	258,821.51	0.92
Company Y	5	5	45,744.84	0.94
Company Y	6	3	85,931.43	0.99
Company Y	7	2	7,397.36	1
Company Y	8	3	5,358.72	1
Company Y	9	1	311.15	1
Company Y	Out of range	2	2,008.67	1
Company Z	1	15	1,264,363.22	0.33
Company Z	2	7	926,019.03	0.58
Company Z	3	8	695,001.15	0.76
Company Z	4	4	557,449.41	0.91
Company Z	5	1	65,982.60	0.92
Company Z	6	3	151,256.06	0.96
Company Z	7	1	130,017.60	1
Company Z	Out of range	1	10,203.66	1

The model's prediction performance for clients with the highest number of inventory outflow records is summarized in Table 12. For Company D, a deviation of up to 20 days was observed, with 506 out of 547 inventory outflow transactions accurately predicted, accounting for 92% of the total collection amount. Similarly, for Company E, 377 out of 417 transactions were correctly predicted with a deviation of up to 30 days, achieving 94% accuracy in the total collection amount. However, for Company F, only 186 out of 279 transactions were accurately predicted with a deviation of up to 40 days, corresponding to 75% of the total collection amount. A deviation of 30 days is considered an acceptable tolerance level for managing the company's cash flow.

Table 12. Performance of the Deep Learning Model – Top 3 Companies with the Highest Number of Transactions

Company Name	Deviation Class	Total Dept	Amount of Inventory Outflow Records	Rate
COMPANY D	1	337	7,622,903.44	0.58
COMPANY D	2	169	4,494,753.02	0.92
COMPANY D	3	38	1,009,367.93	1
COMPANY D	4	2	36,739.61	1
COMPANY D	6	1	24,509.90	1
COMPANY E	1	210	4,145,695.14	0.52
COMPANY E	2	129	2,532,280.07	0.83
COMPANY E	3	38	813,967.47	0.94
COMPANY E	4	21	227,560.30	0.96
COMPANY E	5	6	76,696.34	0.97
COMPANY E	6	7	30,879.75	0.98
COMPANY E	7	5	177,975.77	1
COMPANY E	Out of range	1	118.00	1
COMPANY F	1	56	799,531.15	0.29

COMPANY F	2	53	523,085.33	0.48
COMPANY F	3	42	449,817.20	0.64
COMPANY F	4	35	322,171.44	0.75
COMPANY F	5	30	201,946.66	0.83
COMPANY F	6	25	139,223.02	0.88
COMPANY F	7	13	161,208.82	0.93
COMPANY F	8	9	82,923.43	0.96
COMPANY F	9	4	32,223.07	0.98
COMPANY F	Out of range	12	68,801.15	1

When examining the clients with the highest inventory outflow amounts in terms of value, the model's prediction performance is summarized in Table 13. For COMPANY G, with a maximum deviation of 20 days, 92% of the total collection amount was accurately predicted. For Company H, 76% of the collection amount was accurately predicted with a maximum deviation of 40 days, while for Company I, 80% of the collection amount was correctly forecasted with a maximum deviation of 30 days.

Table 13. Performance of the Deep Learning Model – Top 3 Companies with the Highest Value of Transactions

Company Name	**Deviation Class**	**Total Dept**	**Number of Inventory Outflow Records**	**Rate**
COMPANY G	1	337	7,622,903.44	0.58
COMPANY G	2	169	4,494,753.02	0.92
COMPANY G	3	38	1,009,367.93	1
COMPANY G	4	2	36,739.61	1
COMPANY G	6	1	24,509.90	1
COMPANY H	1	63	3,190,857.31	0.19
COMPANY H	2	51	2,860,401.94	0.36
COMPANY H	3	27	1,965,025.41	0.48
COMPANY H	4	15	4,698,460.84	0.76
COMPANY H	5	9	1,027,517.17	0.82
COMPANY H	6	6	2,756,689.19	0.98
COMPANY H	7	1	252,618.00	1
COMPANY I	1	55	4,619,551.96	0.35
COMPANY I	2	45	4,466,214.39	0.68
COMPANY I	3	13	1,640,028.42	0.8
COMPANY I	4	10	1,939,173.77	0.95
COMPANY I	5	2	275,178.00	0.97
COMPANY I	6	4	312,361.42	0.99
COMPANY I	7	1	48,147.07	0.99
COMPANY I	8	1	82,000.00	1

In this study, another aspect predicted by the deep learning model was the payment method that client companies would use to settle their debts. Accordingly, the model's performance in predicting the choice of payment method was also evaluated. The probability distributions of the predicted payment methods and the absolute differences between these and the distribution percentages of actual payment methods in the inventory outflow records were analyzed separately for each payment method and visualized in the following four charts in Figure 7.

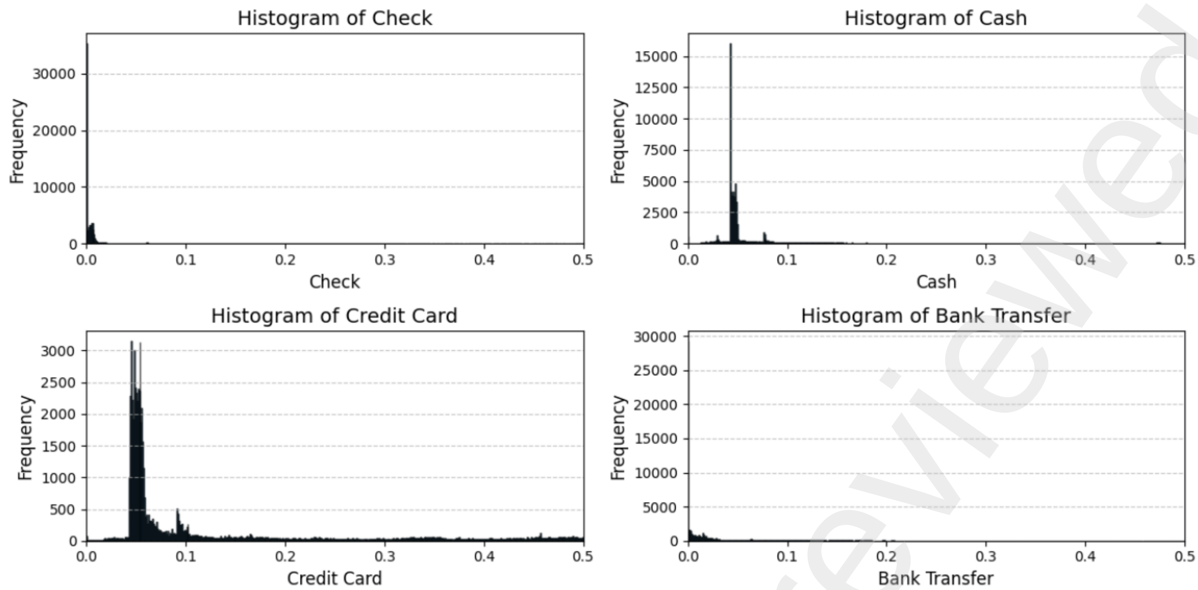

Figure 7. Prediction Accuracy Analysis of Payment Method Types

In the prediction of payment method types (Check, Cash, Credit Card, and Bank Transfer), it was observed that the differences are largely concentrated around zero, indicating that the model has made accurate predictions and that the probabilities are closely aligned with the actual distributions. For Check and Cash payment types, the majority of differences fall within the 0 to 0.1 range, demonstrating the model's high accuracy in predicting these types. For the Credit Card payment type, differences are generally concentrated around 0.1; however, deviations above 0.1 are observed more frequently compared to other payment types, suggesting relatively greater variation in prediction performance for this type. For the Bank Transfer payment type, most of the differences are very close to zero. Overall, the differences across payment method types are minor and are not expected to significantly impact the model's prediction performance.

5. Conclusion and Recommendations

In this study, a deep learning model was developed to understand a company's customer payment behavior and to manage receivables collection processes more efficiently. The model focused on predicting collection periods and methods using stock outflow and collection data from the past three years. These data, derived from the historical financial records of DXXX Machinery Trade Co. Ltd., were processed using the FIFO (First In, First Out) method and transformed into a structure suitable for the model's requirements. The model's input variables included multidimensional information such as collection methods (e.g., check, cash, credit card, bank transfer) based on customers' past payment habits, cumulative collection rates (the proportion of collection methods used as of a specific date), and weighted average collection periods (amount-based average durations for each payment method). This comprehensive dataset enabled the model to analyze customer payment behavior more accurately and achieve high precision in collection forecasts. The analysis results demonstrate that the developed model provided effective predictions with an accuracy rate of 88%, based on a criterion where the difference between actual and predicted payment durations of 30 days or less is considered acceptable and successful. This outcome highlights the model's strong performance in managing collection processes efficiently and its reliability as a valuable decision support tool for businesses.

The high alignment between the model's predictions and actual values for payment methods such as checks, cash, and credit cards demonstrates its consistent and comprehensive forecasting capability across different payment methods. However, some deviations were observed in the collection periods for bank transfers. These discrepancies may stem from the unpredictable nature of customer behavior when using bank transfers or from the model's limitations in forecasting such behaviors. Therefore, further efforts are recommended to improve the model's performance in bank transfer-based predictions and to analyze the inconsistencies in the behaviors of customers who use this payment method in greater detail.

The model not only excels in predicting collection periods but also stands out for its ability to accurately forecast payment methods. When predicting payment types (check, cash, credit card, and bank transfer), the differences between predictions and actual values were observed to cluster around zero, indicating accurate predictions. While high accuracy rates were achieved for checks and cash, slightly larger deviations were identified for credit card payments. Nevertheless, the overall small discrepancies confirm that the model is a strong and reliable tool for both payment durations and methods. This demonstrates the model's ability to successfully capture payment method-specific variations, showcasing its multidimensional forecasting performance.

In summary, the deep learning model developed in this study has proven to be a powerful tool for managing receivables collection processes more efficiently and gaining a better understanding of customer payment behavior. The model stood out with its high accuracy in predicting payment durations in collection processes and demonstrated consistent forecasting capabilities across different payment methods, providing businesses with opportunities to optimize cash flow management and credit policies. Additionally, by offering in-depth insights into collection periods and methods, it contributed to strategic planning processes for businesses. The findings of the study not only demonstrate the strong potential of AI-based approaches in predicting customer behavior but also provide a significant foundation for future research in this field.

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