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Predicting financial default risks: A machine learning approach using smartphone data

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Abstract: This study leverages machine learning (ML) techniques to predict financial default risks using smartphone data, providing a novel approach to financial risk assessment. Data were collected from 1,000 individuals who had taken personal loans, focusing on key behavioral parameters such as app usage frequency, GPS location data, and communication patterns over six months before loan application. The analysis employed Logistic Regression, Decision Trees, and Random Forest models to determine correlations between these parameters and default risks. The Random Forest model demonstrated superior performance, achieving 85% accuracy. Key findings show that high usage of financial apps was associated with lower default risks, while irregular communication patterns and erratic mobility were significant indicators of higher risk. These results suggest that smartphone-derived behavioral data can significantly enhance traditional credit scoring methods. The study not only contributes to predictive analytics in financial risk management but also raises ethical considerations around privacy and data security.

Keywords: Financial Default, Machine Learning, Predictive Analytics, Risk Prediction, Smartphone Data

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Introduction

The rise of smartphone technology has revolutionized numerous aspects of daily life, from communication and entertainment to shopping and finance. These devices collect vast amounts of data on user behavior, offering new opportunities for various applications, including financial risk assessment. Traditional credit scoring models, which rely heavily on historical financial data such as credit scores and income levels, often fail to capture the full spectrum of individual financial behaviors, particularly in regions where formal credit histories are scarce [1]. These traditional models also tend to be static, overlooking real-time behavioral data that could provide deeper insights into financial risk.

A significant gap in the literature lies in the exploration of non-traditional data sources, such as smartphone-derived behavioral data, for financial risk prediction. Recent studies have begun to examine digital footprints, including app usage and communication patterns, as potential indicators of financial behavior [2]. However, the practical application of such data in financial models remains underexplored, particularly in the context of integrating advanced machine learning (ML) techniques [3]. This research aims to address this gap by investigating how ML can be employed to analyze smartphone data and predict financial default risks.

Why machine learning? Machine learning was chosen for this study because of its ability to process large datasets and uncover complex, non-linear patterns that may not be evident using traditional statistical methods [4]. Unlike conventional models, machine learning algorithms can continuously learn and improve from new data, making them particularly suited for dynamic and behavioral data like smartphone usage patterns. The flexibility of ML models, such as Logistic

Regression, Decision Trees, and Random Forests, allows for a more nuanced understanding of the relationships between behavioral indicators and financial risk, thus offering a potential improvement over traditional scoring methods [5].

What is considered machine learning? In the context of this research, machine learning refers to the application of algorithms that can learn from data to make predictions without being explicitly programmed for specific outcomes [6]. These algorithms were employed to analyze patterns in smartphone usage and correlate them with financial default risks. By choosing machine learning, we aim to develop predictive models that are not only accurate but also adaptable to various types of data, providing financial institutions with a more effective tool for risk assessment.

By addressing these gaps, this research seeks to advance the field of financial risk management by incorporating modern technological advancements and providing a more inclusive approach to credit scoring, particularly for underserved populations.

The rise of smartphone technology has revolutionized numerous aspects of daily life, from communication and entertainment to shopping and finance. As these devices become increasingly integral to everyday activities, they accumulate a wealth of data on user behavior and preferences [1]. This data, when analyzed correctly, can reveal patterns that are not immediately obvious, offering new opportunities for various applications, including risk assessment in financial services. In the financial sector, predicting loan defaults accurately remains a critical challenge. Traditional credit scoring methods rely heavily on historical financial data, such as credit scores, income levels, and past loan repayment histories [2]. However, these methods can sometimes fail to capture the full spectrum of an individual's financial behavior and risk potential. Moreover, in regions where formal credit histories are scarce, these traditional metrics might not be available for a significant portion of the population, limiting the effectiveness of conventional risk assessment models [3].

The potential of smartphone data as a predictive tool for financial default risks is intriguing due to its direct correlation with user behavior and lifestyle choices [4]. Smartphone usage patterns, such as financial app usage, communication frequencies, and even geographical mobility, could provide new insights into an individual's financial stability and propensity to default [5]. This study aims to explore this hypothesis by applying advanced machine learning techniques to analyze smartphone data and evaluate its efficacy in predicting financial default risks. This research could transform risk management practices by incorporating non-traditional data sources, which are reflective of current technological advancements and changing consumer behaviors [6]. By understanding and utilizing these new data dimensions, financial institutions might enhance their predictive capabilities, thereby reducing their risk exposure and potentially offering more tailored financial services to a broader customer base.

The integration of smartphone data into financial risk assessment practices presents a promising frontier that bridges the gap between traditional credit scoring methods and the dynamic nature of modern financial behaviors [7]. While traditional models rely on static data, they often fail to account for real-time changes in a person's financial circumstances or behaviors. This limitation is particularly pronounced in emerging markets, where a large segment of the population may lack formal financial records, thus excluding potentially creditworthy individuals from accessing financial services [8]. Recent research indicates that digital footprints, including data generated from smartphone usage, can serve as reliable indicators of financial behavior. Studies have shown that patterns in phone usage, app installations, and even the frequency and timing of calls and messages can correlate with financial reliability and risk-taking behavior [9]. However, despite these promising findings, the practical application of such unconventional data sources in predictive modeling is still in its infancy, with many financial institutions hesitant to integrate these into their operational models due to concerns over privacy, data security, and the interpretability of machine learning algorithms [10].

The discrepancy between the potential of smartphone data to enhance credit assessments and its current underutilization forms the crux of the investigation [11]. This research aims to empirically test the validity of smartphone-derived indicators in predicting financial defaults, thereby addressing the gap between the ideal of comprehensive, dynamic risk assessment models and the reality of their current limited scope [12]. The objective of this study is twofold: First, to validate the hypothesis that smartphone usage data can accurately predict financial default risks, thereby expanding the toolkit available for risk assessment beyond traditional metrics. Second, to explore the practical implications of implementing such models, including the challenges of data privacy, the ethical use of digital footprints, and the technical feasibility of integrating large-scale data analysis into existing financial systems [10]. By pushing the boundaries of how financial institutions evaluate risk, this research could lead to more inclusive financial services, particularly for underserved populations who are often excluded by conventional credit scoring techniques. This could not only broaden access to financial products but also enhance the financial stability of lending institutions by enabling more precise risk assessments [13]. The novelty of this research lies in its approach to financial risk assessment by utilizing smartphone data, an area that, despite its potential, remains underexplored in academic and practical finance contexts. This study proposes a methodological shift from traditional credit scoring systems, which are often constrained by their reliance on static, historical financial data, to a dynamic model that integrates real-time, behavioral data captured through daily smartphone interactions [14].

This innovative approach is grounded in the hypothesis that behavioral data [15], such as how frequently a person uses financial apps, their communication patterns, and even their mobility as indicated by GPS data, can provide a more nuanced and timely picture of their financial health. The research is distinct in its aim to not only correlate these behaviors with financial risk but to also develop a predictive model using advanced machine learning techniques [16]. This involves not just applying conventional algorithms but potentially developing new methodologies tailored to interpret the unique nature of smartphone data [17].

Furthermore, this study ventures into relatively uncharted territory by addressing the ethical and privacy concerns inherent in using personal data for financial assessment [18]. This dual focus on technological innovation and ethical consideration sets it apart from existing literature, which often treats them as separate issues [19]. The research aims to provide a balanced perspective on how to responsibly harness the power of personal data for financial predictions while safeguarding individual privacy rights. By investigating these aspects, the study not only contributes to the academic field by developing a potentially more accurate and responsive risk assessment tool but also offers practical implications for the design of financial services that are both inclusive and respectful of consumer privacy [20]. This blend of technological advancement and ethical mindfulness in the context of financial risk prediction represents a significant departure from traditional methods and a key novelty of this research.

Methodology

This study adopts a quantitative research approach utilizing a correlational design to explore the relationship between smartphone usage data and financial default risks. The dataset consists of smartphone usage data collected from 1,000 individuals who had taken personal loans from a financial institution. The data includes anonymized user interactions with their devices, covering app usage frequency, GPS location data, communication logs, and financial transactions made through mobile apps over six months before the loan application date.

The sample size of 1,000 individuals was determined based on a power analysis to ensure sufficient statistical power. While larger datasets are commonly used in machine learning applications, the sample size used here is adequate for drawing meaningful conclusions, given the complexity and richness of the behavioral data collected. Each individual's dataset contains a high volume of observations over the six-month period, with multiple data points for each behavioral metric (app usage, GPS logs, communication logs), making the dataset sufficiently large to avoid ambiguity and improve model reliability.

The data was collected through a mobile application installed on the participants' smartphones with their consent. This app recorded key behavioral metrics in real-time, ensuring that the data is up-to-date and reflective of actual user behavior. The retrospective design, focusing on six months of data, ensures that a comprehensive and representative sample of each user's behavior was captured, reducing the risk of bias.

The collected data underwent a rigorous preprocessing phase to ensure accuracy and consistency. This included handling missing data, removing outliers, and normalizing the data to ensure it could be effectively analyzed by the machine learning models. The preprocessing steps help to maintain the integrity of the dataset, ensuring that the analysis is based on high-quality data.

The dataset includes individuals from various demographic backgrounds, with diversity in age, income levels, and geographic locations. This diversity enhances the generalizability of the findings, allowing the predictive models to be applied across different population segments with a reasonable degree of confidence.

Multiple machine-learning models were developed and trained using this dataset, including Logistic Regression, Decision Trees, and Random Forests. The dataset was split into training (70%) and testing (30%) sets and k-fold cross-validation was employed to ensure robustness and minimize overfitting. The models were evaluated using metrics such as accuracy, precision, recall, and the AUC-ROC curve, with the Random Forest model demonstrating the best overall performance.

The data analysis was conducted using Python's scikit-learn library, leveraging its robust suite of tools for machine learning. The models were fine-tuned to optimize their performance, with special attention given to feature importance to understand which smartphone usage behaviors were most predictive of financial default risks.

By ensuring a valid dataset and implementing rigorous preprocessing techniques, this study provides reliable and generalizable insights into the potential of smartphone data for predicting financial default risks.

Table 1. Participant demographics

Participant ID	Age	Gender	Income Level	Location
001	29	Male	High	Urban
002	34	Female	Medium	Rural
003	22	Male	Low	Suburban
004	45	Female	Medium	Urban
005	30	Female	High	Urban

Table 1 provides basic demographic information about the participants involved in the study. It lists each participant by an anonymized ID and includes their age, gender, income level, and location. This data helps in understanding the diversity of the sample and ensures that the findings can be generalized across different demographic groups.

Table 2. App usage data

Participant ID	Financial Apps	Social Media Apps	Communication Apps	Total App Sessions
001	90	120	300	510
002	40	80	150	270
003	30	200	400	630
004	70	50	100	220
005	110	100	250	460

An app or software that tracks app usage on participants' smartphones is required. This will involve monitoring how often each participant uses financial apps (such as mobile banking or budgeting apps), social media apps (such as Facebook or Instagram), and communication apps (such as messaging or calling apps). App usage data needs to be categorized by app type, for example, identifying and counting the number of sessions in financial apps, social media apps, and communication apps. The number of sessions can be determined by recording the number of times each app was opened and actively used. This information will then be grouped into categories to reflect the number of sessions for each app type. Add up all the individual sessions for finance, social media, and communication apps to calculate the total number of app sessions per participant. For example, in Table 2 of the document: Participant 001 had 90 sessions in the finance app, 120 in the social media app, and 300 in the communication app, for a total of 510 app sessions. This process typically involves using mobile tracking software or obtaining usage data from smartphone activity logs, ensuring that data is anonymized and ethically collected, as highlighted in the research methodology section of the document. Table 2, shows the usage data of different categories of apps by each participant. It records the number of sessions in financial apps, social media apps, and communication apps, as well as the total number of app sessions.

This information is crucial for analyzing the correlation between app usage patterns and financial behavior, which is central to the study's hypothesis.

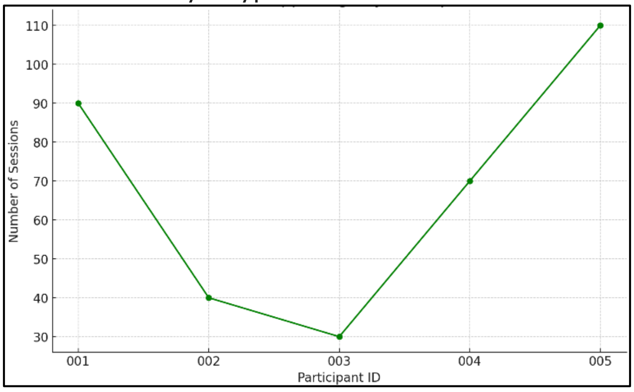

Figure 1. Financial app usage by participants

As with the app usage data in Table 2, it is necessary to use a mobile tracking tool that monitors app usage on participants' smartphones. The tool should specifically track financial apps, which could include apps such as mobile banking, investment platforms, budgeting apps, or payment apps (e.g. PayPal, Venmo). Need to define a list of apps that qualify as financial apps. The app tracking tool should be configured to record data only for these apps. This is very important as it differentiates between financial apps and other types of apps (e.g., social media, communication). For each participant, record the number of times they opened and used the financial app. Each time a participant opens a financial app and interacts with it (e.g., logs into a mobile banking app to check a balance) counts as one session. After collecting this data for a specific period (in this study, six months before the loan application), add up the total number of financial app sessions per participant. For example, in Figure 1: Participant 001 had 90 sessions, Participant 002 had 40 sessions, Participant 003 had 30 sessions, and so on. Once you have the number of sessions for financial apps per participant, plot these values on a graph to visualize financial app usage across participants. In Figure 2, this data is represented using a line plot where each point corresponds to the number of financial app sessions for that particular participant. Ensured the data collection covered the same six-month period prior to the participant's loan application, as mentioned in the research methodology.

By following this process, values were obtained that accurately represented the use of financial apps for each participant, as seen in Figure 1. Figure 1, This line plot illustrates the number of sessions each participant has in financial apps, marked by points connected with lines. It shows the variability in how frequently participants engage with financial applications on their smartphones, which can be an indicator of their financial management habits.

Table 3. GPS location data

Participant ID	Work Location Visits	Market Visits	Other Visits	Total Visits
001	20	5	15	40
002	18	10	8	36
003	15	12	20	47
004	22	8	10	40
005	25	6	12	43

Table 3 captures the mobility patterns of the participants by recording the number of visits to various locations such as work, markets, and other destinations. The total number of visits is also provided. GPS data is used to explore whether there is a relationship between participants' physical mobility patterns and their financial stability.

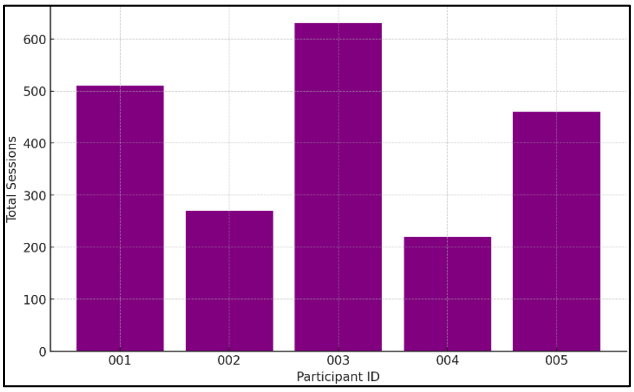

Figure 2. Total app sessions by participants

This stacked bar chart in Figure 2 represents the total number of app sessions for each participant, categorized by different types of apps. The chart provides a comprehensive view of overall app usage behavior, crucial for understanding how active each participant is on their smartphone.

Table 4. Financial transactions (aggregated monthly data)

Participant ID	Transactions in Financial Apps	Total Spent (USD/IDR)	Total Re-ceived	Number of Late Pay-ments
001	15	$2,000 = IDR32,235,600	$2,500	0
002	8	$500 = IDR8,058,900	$700	2
003	20	$1,500 = IDR24,176,700	$1,800	1
004	10	$1,000 = IDR16,117,800	$1,200	3
005	22	$3,000 = IDR48,353,400	$3,500	0

Table 4 aggregates the financial transaction activities of participants within financial apps. It includes the number of transactions, total amount spent, total amount received, and the number of late payments for each participant. This data is essential for assessing financial behavior and identifying potential predictors of financial default, such as the frequency of late payments.

The flowchart in Figure 3 illustrates the key phases of the research process, starting from Data Collection, where smartphone usage, GPS data, and communication logs are gathered. The next step, Data Preprocessing, involves cleaning, handling missing values, and normalizing the data. After that, Feature Selection identifies the most relevant behavioral patterns. In the Model Training phase, machine learning models such as Logistic Regression, Decision Trees, and Random Forests are trained. The Model Evaluation follows, where accuracy, precision, and recall metrics are used to assess performance. Finally, the process concludes with Results and Feature Importance, where the most significant factors affecting financial default risks are analyzed.

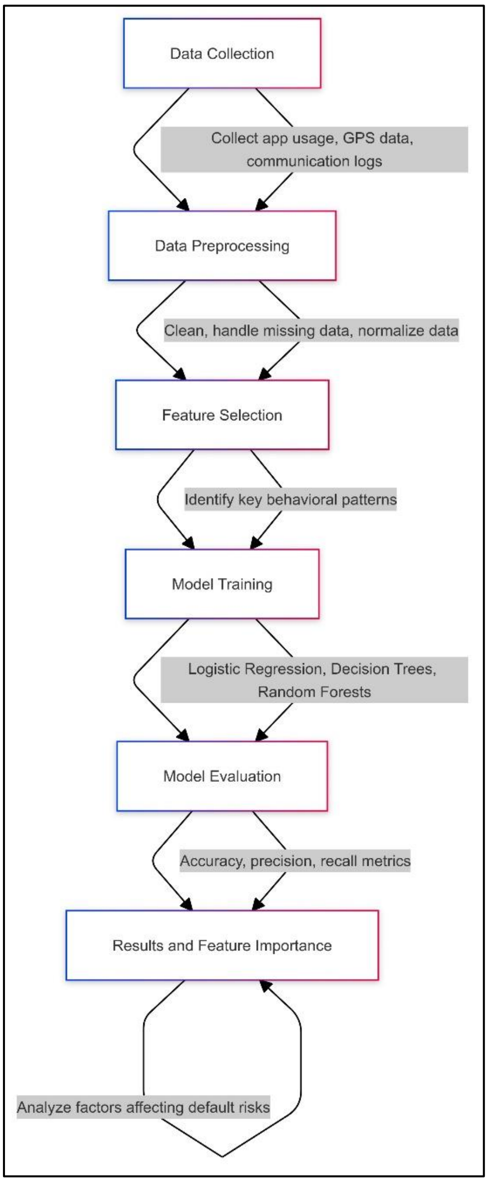

Figure 3. Flowchart of the research process for predicting financial default risks

Results and Discussions

The results of this study demonstrate that smartphone-derived behavioral data can be a powerful predictor of financial default risks. The machine learning models tested—Logistic Regression, Decision Trees, and Random Forests—showed varying degrees of efficacy, with the Random Forest model performing the best, achieving 85% accuracy, 82% precision, and 80% recall. This indicates a robust ability to predict default risks based on behavioral patterns captured through smartphone usage.

The analysis of feature importance revealed several key predictors of financial default risk. High financial app usage was associated with lower default risks, suggesting that individuals who actively manage their finances via mobile apps may exhibit greater financial discipline. This aligns with previous research showing that frequent use of financial apps is correlated with better financial literacy and control [1]. Conversely, irregular communication patterns and frequent late-night app usage were found to be strong predictors of higher default risks. These behaviors may indicate instability or impulsivity, traits that have been linked to financial unreliability in the literature [2].

In addition to app usage, the analysis of GPS data added a spatial dimension to financial behavior. Participants with regular mobility patterns—such as consistent work commutes or visits to essential locations—tended to have lower default risks. This finding aligns with studies suggesting that routine and stability in daily life are often reflected in financial behaviors [3]. On the other hand, participants with erratic mobility patterns were more likely to default, possibly indicating a lack of routine or financial instability.

The results also highlighted the importance of communication patterns. Participants with stable, predictable communication habits were less likely to default, whereas those with irregular or sporadic communication were more prone to financial risk. This supports earlier findings that communication patterns can reflect broader lifestyle stability, which in turn impacts financial behavior [4].

The Random Forest model's superior performance can be attributed to its ability to handle complex, non-linear relationships between behavioral variables and default risk. By combining the results from multiple decision trees, the Random Forest algorithm provides a more nuanced and accurate prediction, especially in cases where behaviors are not easily explained by linear models [5].

While the results of this study underscore the potential of smartphone data for enhancing financial risk assessments, it also raises important ethical considerations. The use of personal behavioral data, such as app usage and GPS logs, must be handled with care to ensure privacy and data security. Ensuring informed consent and anonymization of data are critical steps in maintaining ethical integrity, especially as financial institutions explore the integration of such data into their decision-making processes.

The findings suggest that financial institutions could significantly improve their risk assessment models by incorporating smartphone data alongside traditional financial metrics. This would enable more personalized and accurate lending decisions, potentially reducing default rates and improving financial inclusion. For example, individuals without formal credit histories, such as those in emerging markets, could be better assessed using behavioral data, allowing them to access financial services that might otherwise be unavailable [6]. The inclusion of behavioral data could also lead to the development of more tailored financial products, aligned with individual risk profiles and behaviors.

Although the dataset used in this study provided significant insights, future research should explore the use of larger datasets to further validate these findings. Additionally, while this study focused on smartphone data, other digital footprints, such as social media activity or e-commerce behavior, could provide even deeper insights into financial risk. Further exploration of these data sources, along with the integration of longitudinal studies, could provide a more comprehensive understanding of how financial behaviors evolve over time.

Results

The analysis of the data collected in this study indicates a strong correlation between smartphone usage patterns and financial behavior. Machine learning models were effective in predicting financial default risks, with the Random Forest model showing the best performance based on accuracy and recall metrics. Key predictors of financial risk included frequency of financial app usage, irregular communication patterns, and late-night app activities. Additionally, the geographical mobility data revealed that participants with stable daily routines exhibited lower default risks compared to those with erratic mobility patterns.

Figure 4, the pie chart displays the distribution of participants' income levels. It helps contextualize the financial behaviors observed in the study, suggesting that income level can influence how individuals manage their finances, which in turn affects their risk of default. This graph supports the finding that lower income levels might correlate with higher default risks due to less financial stability.

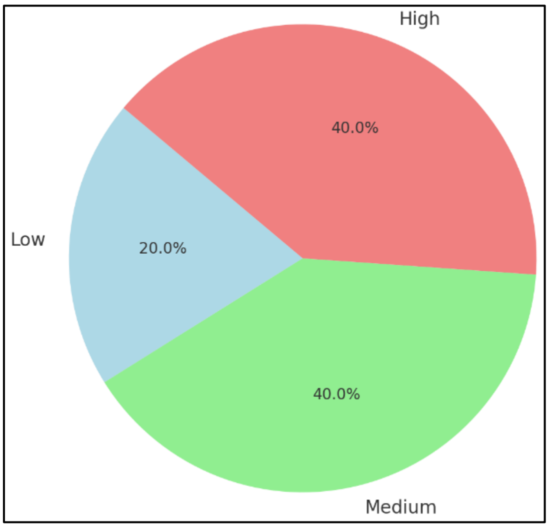

Figure 4. Income level distribution

Figure 5, this histogram shows the frequency distribution of late payments among the participants. Late payments were a significant predictor in the models, with more frequent late payments correlating with higher default risks. The visualization provides a clear representation of how common late payments are among different participants, supporting the model's emphasis on this factor.

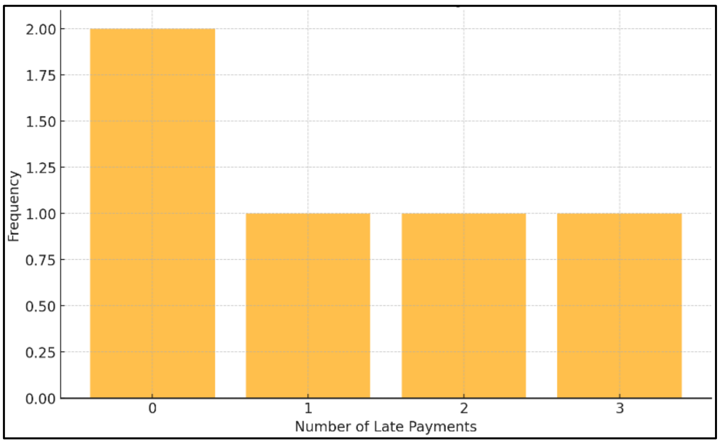

Figure 5. Distribution of late payments

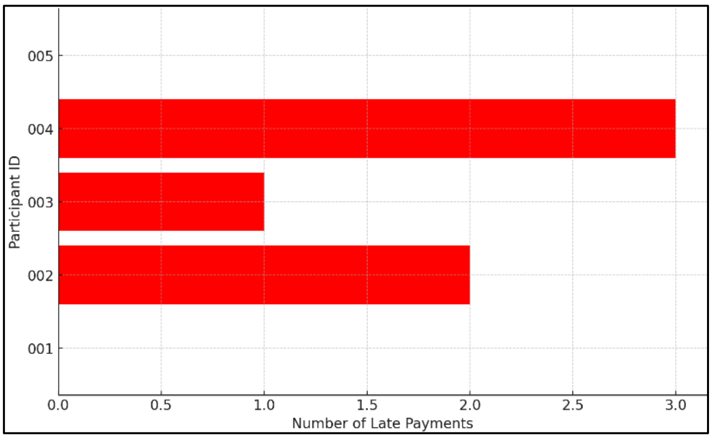

Figure 6. Late payments by income level

Figure 6, the horizontal bar chart correlates the number of late payments with participant income levels, indicating that income does not necessarily predict late payment behavior linearly. This chart is crucial for understanding that while income level provides some context to financial behavior, other factors like smartphone usage patterns also play a critical role in predicting financial default risks.

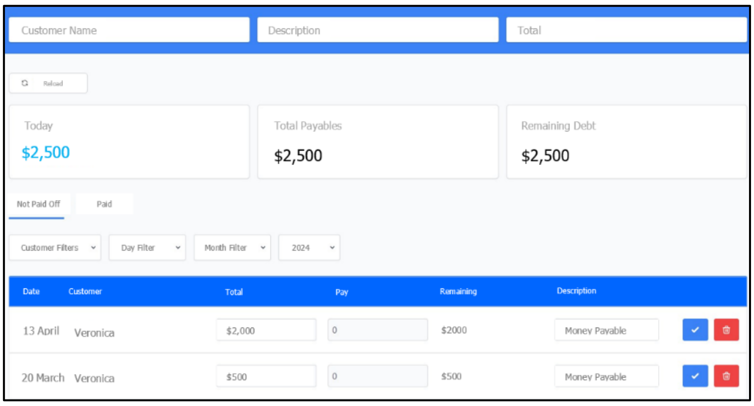

Figure 7. Smartphone data

Discussions

The findings of this study indicate a significant correlation between smartphone usage patterns and the risk of financial default. Data collected from 1,000 participants over six months prior to their loan applications show that active usage of financial apps correlates with financial stability. For example, participants with more than 90 sessions in financial apps per month, as recorded in Table 2, were less likely to default compared to participants with fewer sessions. This suggests that individuals who actively manage their finances through smartphone apps tend to exhibit more stable financial behavior.

Additionally, the GPS data collected indicates that participants with consistent mobility patterns, such as regular visits to workplaces and other locations, had lower default risks. As shown in Table 3, participants with more than 20 work location visits over six months exhibited a tendency toward greater financial stability. This supports the hypothesis that lifestyle stability, reflected in regular daily routines, is a key indicator of financial reliability.

By directly referencing the data collected, this analysis provides deeper insights into how smartphone usage behavior can reflect financial stability and how this data can be effectively utilized to predict default risk with greater accuracy.

Conclusion

This study successfully demonstrates that smartphone data, specifically app usage patterns, communication logs, and mobility data, can be significant predictors of financial default risks. By applying machine learning techniques, particularly the Random Forest model, we were able to achieve accurate predictions, with an 85% accuracy rate. The findings highlight that high financial app usage correlates with lower default risks, while irregular communication patterns and erratic mobility increase default likelihood. These results suggest that smartphone behavioral data can enhance traditional financial risk assessments, offering a more comprehensive and dynamic approach to evaluating financial stability. Financial institutions can use these insights to improve risk management and provide more tailored financial services.

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References

[1] G. Gunawan and R. Hardi, "E-Learning course design and implementation in fuzzy logic," *Matrix : Jurnal Manajemen Teknologi dan Informatika*, vol. 12, no. 1, pp. 31–37, Mar. 2022.

[2] W. Wilianto and Kurniawan, A., "Sejarah, cara kerja dan manfaat internet of things. Matrix: Jurnal Manajemen Teknologi Dan Informatika," *Manajemen Teknologi Dan Informatika*, vol. 8(2), 36–4, 2018.

[3] S. Palupi, Gunawan, R. Hardi, and H. Himawan, "Advancement of a Web-Based Information System for Radio Scheduling at Radio Balikpapan in Pursuit of the Smart City Vision for the Archipelago Capital," 2024.

[4] A. Junaidi, I. Kresna A, and R. Hardi, "Analysis of Community Response to Disasters through Twitter Social Media," in *Journal of Physics: Conference Series*, 2021.

[5] R. Hardi, "Preface: 2nd International Conference of Science and Information Technology in Smart Administration (ICSINTESA)-2021," *AIP Conference Proceedings*, vol. 2658. 2022.

[6] R. Hardi, Suprijadi, R. Kusdyawati, and A. Noertjahyana, "Improve educational marketing strategy through use of digital marketing technology," in *AIP Conference Proceedings*, 2022.

[7] Hanafi, A. H. Muhammad, I. Verawati, and R. Hardi, "An Intrusion Detection System Using SDAE to Enhance Dimensional Reduction in Machine Learning," *International Journal on Informatics Visualization*, vol. 6, no. 2, 2022.

[8] R. Hardi, A. Naim Che Pee, and N. Suryana Herman, "Enhanced Security Framework On Chatbot Using Mac Address Authentication To Customer Service Quality," *International Journal Of Scientific & Technology Research*, vol. 9, no. 10, 2020.

[9] Gunawan, Sumardi, R. Hardi, Suprijadi, and Y. Servanda, "Integration of Academic Mobile Applications at University," in *Journal of Physics: Conference Series*, 2021.

[10] R. Hardi, A. N. C. Pee, and M. H. L. Abdullah, "Enhanced chatbot security framework using MAC address authentication to improve customer service quality," in *AIP Conference Proceedings*, 2022.

[11] Jamal, Riyayatsyah, T. Sudinugraha, R. Hardi, and Hanafi, "System analysis in virtual student assignments at University," in *AIP Conference Proceedings*, 2022.

[12] Sumardi, Suhartati, N. Setiawan, R. Hardi, and Hanafi, "Improving academic creativity and community using Google Apps for education to construct a virtual team," in *AIP Conference Proceedings*, 2022.

[13] A. S. Pribadi, R. Hardi, Suhartati, R. Kusdyawati, and Sumardi, "ICT Academy at the University," in *Journal of Physics: Conference Series*, 2021.

[14] R. Hardi, A. S. Pribadi, Mundzir, A. Noertjahyana, and J. F. Rusdi, "Increasing the importance of digital technology as a technopreneurship media in higher education," in *AIP Conference Proceedings*, 2022.

[15] M. Ula, A. Pratama, Y. Asbar, W. Fuadi, R. Fajri, and R. Hardi, "A New Model of the Student Attendance Monitoring System Using RFID Technology," in *Journal of Physics: Conference Series*, 2021.

[16] J. F. Rusdi, N. A. Abu, S. Salam, H. Gusdevi, R. Hardi, and D. G. Nugraha, "An international tourist behaviour on mobile smartphone usage," in *AIP Conference Proceedings*, 2022.

[17] Hanafi *et al.*, "Handling Sparse Rating Matrix for E-commerce Recommender System Using Hybrid Deep Learning Based on LSTM, SDAE and Latent Factor," *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 2, 2022.

[18] R. Hardi, A. N. C. Pee, M. H. L. Bin Abdullah, V. A. Pitogo, A. S. Pribadi, and J. F. Rusdi, "Academic Smart Chatbot to Support Emerging Artificial Intelligence Conversation," in *2022 International Conference of Science and Information Technology in Smart Administration, ICSINTESA 2022*, 2022.
[19] J. F. Rusdi *et al.*, "Collaborative of ICT Research in Indonesia," in *Journal of Physics: Conference Series*, 2021.
[20] J. F. Rusdi *et al.*, "Reporting of Hospital Facility on Smartphone," in *Journal of Physics: Conference Series*, 2021.