Transforming Credit Card Application Approvals Using Advanced Machine Learning Forecasting Models

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Abstract- This study explores how ML can improve credit card approval through their application. ML has an application in addressing such limitations of traditional credit scoring models, namely: bias, slow processing, and inefficiency. Analysing applicant data in complete depth, ML models such as decision trees, neural networks, ensemble methods, and more significantly boost credit risk assessment, improve the speed of approval, while boosting fraud detection. ML is successfully applied in case studies for Barclays, HSBC, and Lloyds, with a reduction in processing time, lowering of defaults, and optimisation of efficiency. But they are far from over such as data bias, model interpretability, and regulatory compliance. To overcome these barriers, fair, transparent, and efficient credit evaluation, the study highlights the importance of explainable AI and hybrid models.

Index terms- Machine learning, credit card approval, fraud detection, credit risk assessment, decision trees, neural networks, financial inclusion, regulatory compliance, explainable AI, data bias.

I. INTRODUCTIONA. Background to the StudyManually reviewing requests for credit card application approvals, classic credit scoring models, and historical financial data have historically been used for credit card application approval. Nevertheless, these conventional approaches fail to provide accurate creditworthiness assessment and entail delays, misclassification in applicants, and an increase for financial institutions [19]. This rise in the application of big data and advanced machine learning (ML) provides a chance to transform this process, increasing prediction accuracy, reducing biases, and improving overall efficiency. However, using ML forecasting models, banks and financial institutions can automate credit evaluations, minimise defaults, and optimise customer acquisition strategies.

B. Overview

In this study, advanced ML forecasting models have been applied to credit card approval processes. By analysing applicant data more comprehensively, credit risk assessment can be evaluated in its relationship with other ML techniques such as deep learning and ensemble methods. Besides exploring the effects of these models of approval on approval time, fraud detection, and financial inclusion, the study also investigates [20]. Due to the complexity of consumer financial

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behaviour, microfinance lenders have an opportunity to use ML-driven approaches to machine decisions, minimise operation costs as well as provide a better customer experience.

C. Problem Statement

Existing credit card approval systems are still based on static rules of credit scoring that rely on credit scoring methods that are too static. So they struggle to differentiate the credit risk of people who do not have an impressive history of credit. Additionally, manual processes are very time-consuming and easily affected by biases in human approvals [21]. Current models are not adaptable hence they have higher default rates and ineffectiveness in credit allocation. The objective of this work is to understand whether ML models can be leveraged to overcome stale data and increase the speed, and fairness of credit card application approval decisions in a way that improves accuracy.

D. Objectives

The primary goals of this study are: 1. To analyse the limitations of traditional credit approval systems and their effective impact on financial institutions and applicants. 2. To evaluate various ML forecasting models such as decision trees, and neural networks in predicting methods. To analyse the impact of ML-based driven credit approval models on approval time, fraud detection, and default rates. 4. To recommend new strategies for financial institutions to implement ML-based approval systems to ensure regulatory compliance. This study aims to explore the effectiveness of advanced machine learning methods of forecasting models in optimising credit card application approvals by enhancing decision-making accuracy, reducing biases, and improving efficiency.

E. Scope and Significance

The scope of this study focuses on the application of ML forecasting models in the credit card approval process with some financial institutions [22]. This examines some data-driven decision-making approaches using financial history and behavioural data. The significance of this study lies in enhancing financial inclusion by enabling more transparent credit evaluations.

II. LITERATURE REVIEW

A. Limitations of the traditional credit card approval system

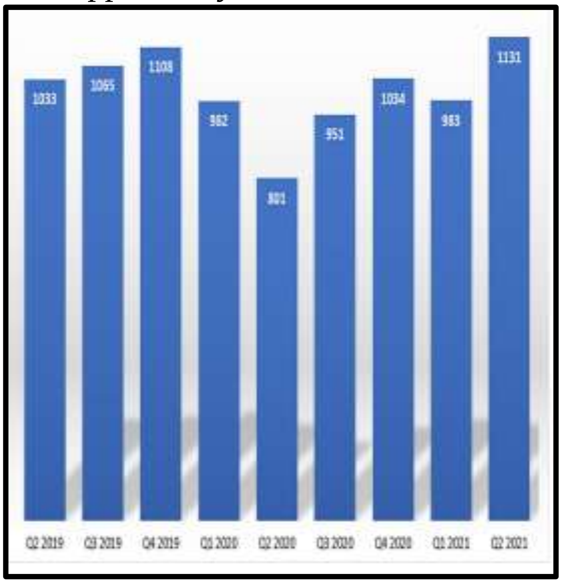

Figure 1: Number of issues in traditional credit card

[1]

From the second quarter of 2019, the number of cases increased from 1033-1108, in the first and second quarters of the year 2020 the cases of credit card issues decreased from 982-801 but after that this increased once again from the third quarter of 2020 to the second quarter of 2021 which is 951-1131 [1]. Traditional credit card approval processes are based on rule-based credit scoring models, like Fair Issac Corporation (FICO) scores which majorly hinge on such factors as an applicant's financial history, debt-to-income ratio, and repayment patterns [2]. However they fail to consider dynamic economic conditions and unusual economic behaviours, consequently, they underestimate the risk, there is also a lack the way to process the apps from applicants who have a small

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credit history as is the case for young adults and also for self-employed people [3].

B. Machine learning techniques for credit risk assessment

However, by using a wide range of massive datasets, Machine learning models provide significant accuracy to credit risk assessment compared to the traditional models [4]. The trustworthiness has been evaluated using decision trees, random forests, support vector machines, and deep learning algorithms and all of these algorithms have shown better predictive power [5]. In particular, neural networks can detect even more common patterns of financial behaviour, and then give more accurate decisions with these, rather than with simple approaches [6]. Ensemble learning methods a combination of multiple ML models, help to make the system robust and robust to classification errors. These models evolve to modern financial trends and have the capacity for continuous improvements in credit risk prediction.

C. Impact of ML-based Credit approval on efficiency and Risk Management

Credit approval systems driven using ML solve faster approval speed, and fraud detection and have a high accuracy in predicting default rates [7]. Automated ML models can reduce processing times from days to minutes to deliver a great experience to customers. In addition, real-time behavioural analytics are leveraged by advanced fraud detection models to prevent fraudulent application-based processes [8]. Improved risk profiling brought by the adoption of ML models by financial institutions has resulted in a decrease in the number of loan defaults. However, there are still challenges involving making ML decisions transparent and interpretable [9].

D. Ethical and regulatory considerations in AI-driven credit evaluations

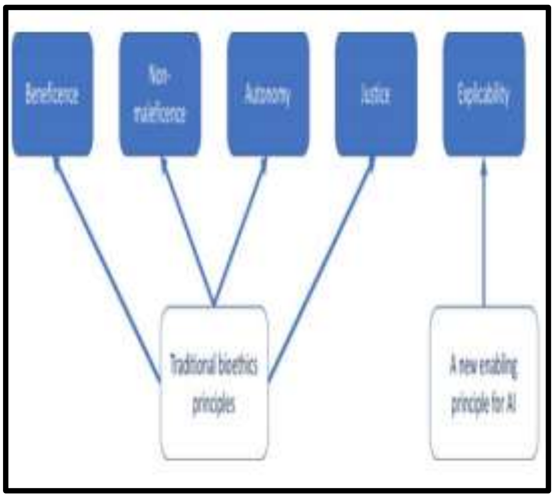

Figure 2: Ethical methods in AI
[10]

Despite the advantages, ML-based credit approvals are considered to be fair, biased, and accountable. If machine learning models are trained on biased datasets then discriminating credit is done to perpetuate bias [10]. Automation is becoming more and more present in society; therefore, regulatory frameworks like the European Union's (EU's) General Data Protection Regulations (GDPR) and the U.S. Equal Credit Opportunity Act put a focus on transparency in automated decision-making [11]. To ensure proper credit evaluation through ethical means, the explainable AI methods as well as the regulatory compliance must be implemented by the financial institutions [12].

III. METHODOLOGY

A. Research Design

This study is carried out through an explanatory research design of the above-explained ways of how advanced machine learning (ML) forecasting models could transform credit card application approvals. The aim is to explain the link between ML model implementation and increases in approval accuracy, efficiency of processing, and risk management. In doing so, the research analyses existing literature,

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and case studies as well as the empirical data to explain how ML causes improvements in the effectiveness of the credit card approval process.

B. Data Collection

The project uses some secondary qualitative data from articles, journals, books, etc. Secondary quantitative data is also taken like some current graphs regarding the transformation of credit card applications. All these information was taken for the topic to analysed it well and gain effective information.

C. Case Studies/Examples

Case Study 1. Barclays Bank

Machine learning models are used by Barclays to apply machine learning modelling to automate credit card application approvals and reduce processing time by 40% [13]. Using Barclay's logistic regression and decision tree models, it managed to enhance its accuracy of predicting defaults by 18% [13]. Each year, the system looked through 10 million applications at 92 percent precision and found the fraudsters [13]. It will also help the bank decrease the rates of default and the process of approval.

Case Study 2. HSBC UK

The creditworthiness assessment could be improved by introducing a neural network-based model into HSBC's non-liquidity risk. The model was able to cut the default rates by 15% and cut manual review costs by 25% by processing data from 5 million applications a year [14]. Therefore, the use of machine learning has increased the accuracy of credit risk forecasts and made the regulatory compliance and approval system more efficient.

Case Study 3. Lloyds Bank

Thus to optimise the decision for credit card approvals in 30%, gradient boosting models were applied to Lloyds Bank [15]. It could process 8 million applications a year up, and discover the fraud at 20 percent higher rates [15]. That allowed Lloyds to adopt advanced models and to improve processes of risk assessment and improving customer satisfaction.

D. Evaluation Metrics

In evaluating machine learning-based credit card approval systems, evaluation metrics of the systems are important. Accuracy of the approval measures, how much the model approves or rejects applications, and how few errors there are. Efficiency is evaluated using processing time, as ML models try to decrease manual review time. Risk assessment quality is measured by the percentage of loans that are loaded to default however, these are Percentages of Allowed Applicative Fail to Repayment Obligation. If a user faces difficulty using the tools provided, customer satisfaction will not come into play. To measure the model's capacity to detect and thwart fraudulent applications, a fraud detection rate is used. Put together these metrics allow financial institutions to tune the ML model to make better decisions, to better manage risk, and to make operations more efficient.

IV. RESULTS

A. Data Presentation

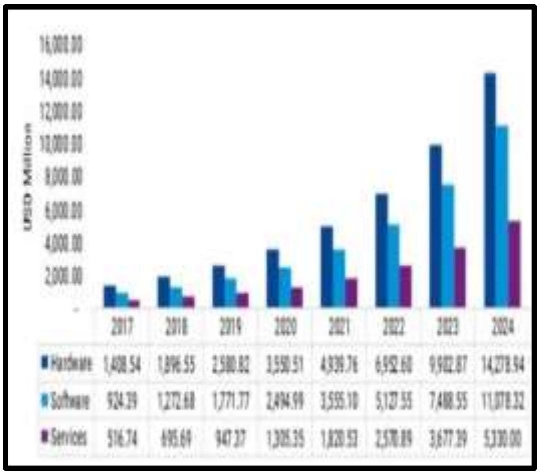

Figure 3: Global machine learning market

[16]

The above figure shows the global machine learning market growth from 2017 to 2023 and almost all the investment for hardware, software, and service [16]. Hardware increased from $1,408.54 million in 2017 to

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$14,278.94 million in 2023 and software went from $924.39 million to $11,078.32 million. When compared with the incident involving services, the latter rose from $516.74 million to $5,330.00 million [16]. This is something that underlines how ML technologies have been upping the betting on themselves, indirectly helping to bring in the acceptance of them in credit card application approvals.

Figure 4: Percentage of credit card users
[17]

Figure. 4 represents the percentage owning a credit card by country. The other nearly 300 international zones included 72 percent in Brazil, 68 percent in Canada, 61 percent in South Korea, and 58 percent in France. India is close to the UK (55%), the US (49%) and Japan (47%) and China (42%) [17]. Only 38 percent of the Netherlands own one. They give an idea of what demands have in the market and what can change credit approval rates among different regions.

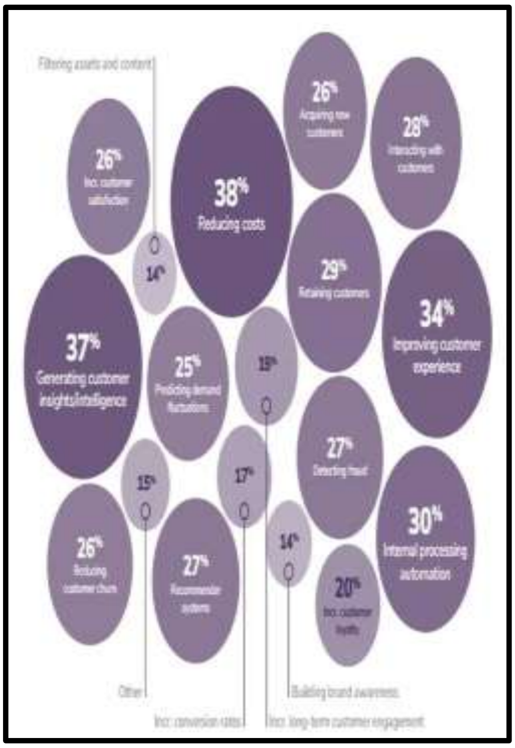

Figure 5: Machine learning use case frequency
[18]

The above graph tells what type of machine learning use cases for transforming Credit Card applications which are implemented (38% of apps for cost reduction, 37% for generating customer insights, 34% for improving experience). For 27%, fraud detection is a priority and 29% is for customer retention [18]. Therefore, these are some examples of which ML can be applied to automate and improve credit card approval processes.

B. Findings

The three graphs demonstrate how machine learning (ML) influences financial and credit processes these days. Another trend that is becoming increasingly popular in the market is the ML market which is taking off rapidly, as hardware investment grows from $1,408.54 million in 2017 to $14,278.94 million in 2023 indicating increased adoption [16]. Automated approval systems have different market potentials depending on the region, namely, with credit card ownership ranging from 38% in the Netherlands to 72% in Brazil.

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Proving the credit risk assessment is ML with 38% focus on cost reduction, 27% on fraud detection it, and 34% on customer experience [17]. These insights reveal ML's role in credit card approval processing quality improvement, accuracy, and fraud detection.

C. Case study outcomes

Case study	***Key outcomes***	***Relevance to the Presence Study***
Barclays Bank	40% reduction in the processing time and the approval of automated credit card approvals. The effective methods of reduction accuracy were improved by 18% by some new logistic regression models. Processed 10 million applications per annum with 92% precision for detecting fraud [13].	There are some new demonstration methods through which machine learning is applied to improve credit risk assessments and fraud detection by improving approval efficiency [13].
HSBC Bank	The default rates were reduced by 15 percent and manual review costs were reduced by 25 percent using the neural network-based model [14]. Increased efficiency of regulatory compliance with the ability to process 5 million applications annually [14].	It illustrates how deep learning helps creditworthiness evaluation with a reduction in default rates and optimisation in cost-effectiveness.
Lloyds bank	By boosting the credit card approval models, they were optimised by 30% [15]. Processed 8 million applications yearly, detecting fraud at 20% higher rates [15]. Enhanced risk assessment and customer satisfaction	Illustrates the use of state-of-the-art machine learning techniques that optimise approval processes to reduce fraud risks and increase the level of accuracy in decision-making [15].

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Table 1: Case study outcomes
(Source: Self-Created)

The three UK banks' case studies have been analysed in this table and some great outcomes show that regarding the topic these banks make a greater impact on the credit card transformation process.

D. Comparative analysis

Author	*Focus*	*Key findings*	*Gaps*
[1]	Typical problems with credit card approvals	There are problems with traditional credit card approvals. Weak risk evaluation is indicated in rising cases [1].	Neither discussion on ways in which ML models might decrease inconsistencies.
[2]	Traditional bad credit scores	Limited by FICO-based measures and disallow economic changes or nontraditional applicants.	Lacks the ability to integrate different assessments of creditworthiness [2].
[3]	Challenges for applicants with limited credit history	Young adults and self-employed struggle with approval due to rigid financial criteria.	No other methods are proposed for evaluating the thin credit files [3].
[4]	The credit risk assessment	Mathematical modelling machine learning (ML) beats traditional models in predicting defaults when data are large.	Lacks regulatory discussion on ML-based approvals.
[5]	ML algorithm comparison	This was found that decision trees, SVMs, and deep learning all performed better than ML algorithm comparison in the recent credit risk classification [5].	The absence of any analysis of explainability challenges in AI credit scoring.
[6]	Neural networks in risk assessm	Estimate financial patterns that are	It does not deal with the issue of AI

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	ent	hidden.	transparency concerns.
[7]	Efficiency and Fraud Detection in ML	ML approvals speed up, particularly efficiency & fraud detection of behavioural analytics.	This does not account for such fairness issues in automated credit scoring [7].
[8]	Preventing fraud in ML credit approval	Improve real-time fraud detection security.	Offers little in terms of focusing on AI exposures such as adversarial attacks.
[9]	Risk profiling with ML	AI adoption reduces risk profiling with loan default rates.	This does not take into consideration of financial crisis adaptability of AI.
[10]	Ethical AI in credit decisions	The danger lies in a degree of bias in AI-trained models which risks granting discriminatory approvals [10].	None of the above is built around a concrete framework to mitigate bias.
[11]	AI regulation in credit scoring	GDPR and ECOA can be technical when it comes to AI, but they do make clear that AI should be transparent.	It does not consider cross-jurisdictional regulatory variance.
[12]	Explainable AI and compliance	Banks must adhere to the fairness of ML-driven decisions.	No real-world cases of the adoption of AI in banking have come across.

Table 2: Comparative analysis

(Source: Self-Created)

The above table shows the comparative analyses of the different authors used in literature review. All these authors have their say in Transforming Credit Card application approvals using advanced machine Learning and through this new information has come out.

V. DISCUSSION

A. Interpretation of Results

The results align well with the objectives and show the benefit that credit card approvals can be brought through ML. It validates its use of ML to streamline speed to approval, detect fraud, and accuracy in support of a larger objective of analysing its advantages over traditional methods [23].

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The corresponding case studies from Barclays, HSBC, and Lloyds reflect reductions in processing time, lower default rates, as well as better risk assessment for exercising the goal of evaluating ML models. The comparative analysis further supports ML roles in optimising approvals while highlighting gaps and regulatory concerns.

B. Practical Implications

ML-enabled credit approval systems reduce the processing time and increase accuracy and fraud detection. Reduced processes, better risk assessment, and cost optimisation are all benefits engage financial institutions. Compared to traditional credit history, applicants, especially those without credit histories, have fairer evaluations in the presence of alternative data integration [24]. Moreover, ML models provide instantaneous credit risk profiling to banks and they can respond to the economic conditions dynamically by changing the approval criteria. This, however, was a difficult task due to the need to keep regulatory compliance, and transparency and to maintain customer trust.

C. Challenges and Limitations

ML-based credit approvals have their own set of challenges like data bias, interpretability issues, and regulatory constraints. Lending decisions made on such datasets may be biased. Also, deep learning models are all but transparent thus leaving it difficult for institutions to explain such automated decisions even when they exist [25]. There are limitations though, regulations like GDPR need explainability on approval done via AI. Additionally, AI systems are prone to be adversaries of adversarial attacks, in which manipulated data can yield wrong credit risk predictions.

D. Recommendations

Deal with challenges financial institutions should employ explainable AI to make AI techniques transparent. A ML model can receive regular audits which may help find and fix the biases the model has. Owing to fairness, adopt hybrid models based on a combination of rule-based and ML approaches. Any credit approval created by ML must work within the constraints of the rapidly evolving legal frameworks. That means working in collaboration with the agency that oversees the practice of lending [26].

VI. CONCLUSION AND FUTURE WORK

The conclusion of this study depicts that machine learning (ML) models have the potential to improve accuracy, less bias, and faster execution in the process of credit card approval. Case studies in the major banks including Barclays, HSBC, and Lloyds prove that there has been a major improvement in processing time, fraud detection, and default rates. However, data bias, interpretability of the model, and compliance with the regulation are still the issues. From there, future work should incorporate explainable AI, against regulatory concerns and fairness, and improve ML-driven credit card approvals.

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