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DEVELOPMENT OF A LOAN ELIGIBILITY PREDICTION APPLICATION USING MACHINE LEARNING ALGORITHM

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Abstract

Financial institutions can automate and increase the accuracy of lending decisions by utilizing machine learning to anticipate loan disbursements. Conventional approaches rely on manual review, which lengthens processing times and raises the possibility of errors. According to recent reports, between 10 and 15 percent of loans made by financial institutions in developing nations default annually, resulting in significant losses and disrupting credit flow. This emphasizes how predictive technologies that can evaluate loan eligibility and default risk before to distribution are necessary. This study aims to employed supervised learning models to forecast whether a loan will be accepted and disbursed. The dataset included variables such as income, credit score, employment status, loan amount, and repayment history. Models including Logistic Regression, Random Forest, Support Vector

Keywords: Loan Disbursement, Machine Learning, Evaluation Metrics, Feature Selection

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Machine, and Decision Tree (DT) were trained and evaluated. Model performance was measured using sensitivity, specificity, accuracy, F1-Score and AUC. The DT model achieved the highest sensitivity of 80.39%, specificity of 83.33%, accuracy of 82.05%, F1-Score of 83.97% and AUC of 83.20% showing strong performance in identifying data pattern. The results demonstrate that machine learning provides an efficient and consistent approach for predicting loan disbursement outcomes, supporting data-driven lending and better credit risk management.

Introduction

There has been a great improvement in the financial sector over the past decade. The ability to use technology and the ability to use big data for training and testing of Machine Learning models make it tremendous [1-3]. Bank customers no longer rely on the traditional physical appearance in the bank to carry out transactions, including loans [4]. Because of the technological advancements, many financial institutions have started deploying software applications to help them manage their processes, which helps to achieve speed, efficiency, and automation of the majority of the bank processes [5]. One of these transformations is the evolution of the loan approval process [6]. Which was once a lengthy, subjective, and time-consuming exercise dependent on manual verification and human intuition can now be approached with reliable and scalable data-driven technologies [7]. This shift in technology is basically for reshaping risk management and business operations for banks and other financial institutions [8]. Large volumes of Digital records, robust databases, and advances in computational power make it possible to analyze vast datasets quickly [9]. As a result, the integration of machine learning into the workflow of loan eligibility prediction has moved from academics to business [10]. As a result of this development, its challenges came with it and it is important to recognize why the evolution of machine learning has been so impactful in this domain. Traditional loan evaluation systems have their drawbacks [10]. First, these systems can be time-consuming because they requiring manual processing. Bank officers must look through paper or digital documents, analyze incoming and outgoing statements, check credit histories, and mistakenly subjective judgments [11]. Second, human-centered processes are biased and inconsistent, which can introduce inaccuracy [12]. Third, manual assessment is difficult to scale as application volumes increase, such as during economic crises [13]. While the regulatory bodies are making sure to ensure fairness and objectivity, even the most careful and diligent human data analysts may apply inconsistent criteria, particularly when under pressure or when interpreting ambiguous applicant data [14]. This creates inefficiencies not only for loan applicants, who face prolonged waiting times, but for the lending institution itself, which faces elevated operational costs and risk

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exposure due to human error [15]. The financial repercussions of erroneous and biased decisions can be terrible, potentially resulting in higher loan repayment default rates and a loss for the financial institution [16]. To nullify the bias, subjectivity, and error involved in the manual process, ML has emerged as a tool for building models that will be able to recommend applicants for loans by learning from information about the applicants [17]. ML is trained and tested using previous data from bank customers who have taken loans in the past and either repaid or defaulted. These ML models can increase the number of applications processed in a day [18-20]. ML is promising accurate, unbiased loan distribution and an efficient loan distribution system.

Loan was predicted using machine learning and deployed on the web by [3, 21]. Machine learning approaches offer not only improved predictive performance but also flexible operations [22]. ML-trained model can be used to process millions of applications in a day based on the processing power of the computer being used. After a model has been developed and deployed, a framework can learn new data, train, and redeploy the model [23, 24]. This will improve the accuracy of the existing model and business value. The current loan-eligibility model used numerical data with the following features which can be categorized into Demographics data, which include age, gender, marital status, and education status, financial data, which include income, dependents' income, credit history and other features such as employment status, loan amount requested and the purpose of the loan [25, 26]. All these features give us the financial information about the applicants and their capabilities to repay the loan. A typical ML modeling process starts with data collection. These datasets can be either numerical datasets, images, or videos. This is followed by pre-processing the dataset for modeling. This process involves cleaning, filling in missing records, splitting the data, and even feature selection. Repositories like Kaggle and UCI repository consist of available datasets that can be used for ML experiments. The dataset is then passed into an ML algorithm like Logistic regression, Support Vector Machine, or any other supervised learning algorithm. Feature selection may help us select the most relevant features in the data. The model captures hidden relationships in the data, which will later be used for predictions [27]. The ability of a system to continuously monitor the system's outcome is an advantage of a data-driven system. The system can identify loans that are repaid or not repaid and feedback the loan back into the system for another set of training [28]. This allows the system to adopt the loan taker's behaviors over time, and it will adjust itself to it. In a manual system, this feedback loop is difficult to implement. This serves as one of the strengths of this research. Supervised machine learning algorithms have been used to predict loan eligibility. The most used ML algorithms are Naive Bayes (NB), Decision Trees (DT), Logistic Regression (LR), Support Vector Machine (SVM), K-nearest Neighbor (KNN), and

Random Forest (RF). LR is known for its transparency and simplicity. Probabilistic predictions are its major strength, and it is easy to interpret for loan disbursers and financial institutions [29]. DT work by a sequence of human reasoning and split the data based on the important features that can suffer from overfitting [11]. KNN classifies applicants based on their similarity to previous records, which can yield strong results with well-clustered data but may not provide high accuracy in high-dimensional settings [29]. RF, an ensemble method of multiple decision trees, balances accuracy with robustness, overcoming many of the bias and variance issues inherent in single-tree approaches. LR has proven to be the best performing model because it delivers high accuracy over many geographical datasets and even moderately sized datasets [30, 31]. The careful selection and tuning of the machine learning model are therefore vital to the system's operational success. The advancements of other methods in ML, and also the emergence of explainable artificial intelligence tools, help us to identify the potential ability of the system. But for now, with the nature of the current research, which involves numerical datasets, supervised learning models remain an efficient and effective step toward automating the loan distribution system. It is not sufficient for predictive models to exist solely in data science computing environments. For usable institutional benefit, these models must be embedded into user-friendly platforms. To make these models usable for users, ML Development tools such as Python's Flask and Django library can be used for the deployment of ML models to the web for the use of financial institutions. Flask is a library meant to work within an HTML environment, and the models are added to the code via paths, and features are entered into the web interface; thus, predictions are made [32]. These cloud-based applications can be hosted on available web hosting platforms like Heroku and Render. These platforms provide feedback and suggest model improvement . Even though the operational benefits of automated loan eligibility prediction are important, ethical considerations remain very important. Financial decisions have profound implications for individuals and institutions. If not properly managed, automated systems may inadvertently encode or reinforce biases present in historical data. Disparities in approval rates according to gender, race, or socioeconomic status will not be acceptable and are subject to increasing regulatory scrutiny. As a result of these, modern loan eligibility models must be built with the following attributes, like transparency, fairness. Regular audits, bias detection processes, and stakeholder reviews are essential, as is ongoing attention to privacy and data security. This research aims to develop and compare. ML model that can predict if a loan will be paid or defaulted.

Literature Review

If you had asked a bank officer twenty years ago how loans were granted, the answer would have been a story about stacks of paperwork, long investigative interviews, and a

gut feeling honed by decades on the job. Experience, intuition, and an eye for red flags were valued as much as, if not more than, the numbers on a balance sheet. For better or worse, human beings were at the center of every decision. For decades, this approach was sufficient, or at least, it was the best available. Today, we are living through an era where that familiar story is quickly being rewritten. Banks, both small and large, now face huge volumes of applications and customer expectations for fast, fair, and transparent service [4, 14]. Paperwork has given way to digital records, and lengthy waits have given way to near-instant decisions. At the root of this transformation is not only digitization, but also the rise of machine learning a toolkit that is changing the game for how risk, eligibility, and creditworthiness are evaluated [33]. The journey from manual procedure to algorithmic lending did not happen overnight. Early efforts were a blend of optimism and growing pains. Banks and researchers tried adopting rule-based systems, essentially hard-coded checklists for approval criteria [34]. Some used simple statistical models, the most prevalent among them being logistic regression, because it naturally fits problems where there are two possible outcomes: approved or denied [35]. These early systems brought speed, but their sense of bias and appropriateness was only as good as the human rules that shaped them. If the rules missed context or reflected unconscious bias, the problems persisted. Moreover, once everyone realized the limits of rote checklists, it became clear that no two applicants are exactly alike, nor are any two loans. Real life often defied simple categorization. The scope of data and computational capability expanded gradually, and with it, more flexible approaches came into existence. Decision trees offered the ability to classify borrowers into one or two categories based on patterns found by the data itself [3, 36]. In concept, these trees mirrored how a human might ask a series of questions, but they could process far greater complexity and scale. However, single trees brought with them the risk of overfitting too much faith in the quirks of earlier applicants. Once again, the field adapted. The RF method, which simply means growing lots of decision trees and pooling their opinions, emerged as a pragmatic solution [11]. Countless studies and real-world pilots have shown that random forests make predictions that are less wobbly and more realistic than their single-tree ancestors. K-nearest neighbor joined the conversation as well [19], appealing with its down-to-earth logic: if new applicants closely resemble people who were approved or denied in the past, it stands to reason that their likely outcome will match too. However, the simplicity of this technique comes at a computational cost when applications number in the thousands or millions, a reality not lost on bankers with busy databases. Of course, the story does not end with these classical tools. The past years has seen experimentation with “boosting” approaches and deep learning [2], especially in institutions with enough data and technical talent to support models with hundreds or thousands of variables. Sometimes,

these sophisticated models edge out their simpler cousins, especially when signals hidden in the data are subtle or nuanced. But with great power comes greater risk: increasingly complicated models can be a black box, making their predictions difficult to explain to customers or to regulators. Seasoned practitioners will quietly admit that most of the automations in machine learning applications comes not from the algorithm itself, but from the data that feeds it. Raw loan application datasets are rarely complete: fields are missing, spellings may be inconsistent, and applicant circumstances defy tidy boxes. Before any clever prediction can be made, a great deal of time goes to cleaning, normalizing, and, crucially, figuring out which data points actually matter. For instance, some variables routinely crop up as strong predictors: income, current debts, property value, and length of employment are stalwarts. Yet, overloading a model with every available field can ironically make it worse, not better. Counter-intuitively, models sometimes benefit from ignoring variables that add noise or ambiguity. Crafting "features" that combine or reinterpret raw fields such as calculating a debt-to-income ratio or encoding whether an applicant has a stable job history often delivers better results than simply tossing raw numbers to the algorithm. This is an art as much as it's a science, one best learned through trial, error, and the insight that comes from close study of both data and domain. Once models are built, the question naturally arises: how well do they work? Accuracy is an obvious metric, but in lending, it is not always the most meaningful one. Imagine a model that says "approved" all the time in a dataset where most loans are approved. It looks impressive but is genuinely useless for distinguishing risk. That is why best practice involves using confusion matrices and related metrics such as precision, recall, and the area under the ROC curve. These metrics help banks truly understand where models are making good calls, identifying worthy borrowers, as well as where they are prone to false negatives or false positives. In real deployments, logistic regression and random forest models often provide the best compromise between transparency and predictive power. K-nearest neighbor and simple decision trees may still have their moment, especially with smaller or cleaner datasets, but they are gradually overshadowed by ensemble and boosting methods as the industry builds toward sophisticated, scalable systems. Despite all technical achievements, the literature and day-to-day practice highlight a recurring, fundamental truth: lending has real consequences on real lives. The ethical dimension of automated lending, once considered an afterthought, has become central. Stories abound of algorithms that propagate historic biases, unintentionally discriminating against protected groups or reinforcing patterns of exclusion. This realization has spurred a wave of research and regulatory guidance around bias detection, model explainability, and transparency. Banks are learning, sometimes the hard way, that any system that cannot "show its work" or offer

clear rationales for decisions is at risk of losing trust both from customers and watchdogs. A rush to chase higher accuracy must always be weighed against whether a system aligns with social responsibilities and the principle of equal opportunity. Finally, what separates a successful project from an academic curiosity or a cool experiment in a lab is the ability to put machine learning into practice. With accessible programming tools and web frameworks, small teams can now build web applications that connect models to bank staff or even to customers directly. A well-designed interface, backed by robust code, means that predictions are not just a technical marvel but an everyday tool that speeds up service and, at best, levels the playing field for everyone involved.

Data Collection

The dataset is sourced from publicly available repositories such as Kaggle, containing historical loan application records. The dataset contains 1,555 records of two classes. Those that defaulted are 768, while those who repaid the load were 787.

Data Attributes:

The dataset contains features like Applicant's Income, Co-applicant's Income, Loan Amount, Loan Amount Term, Credit History, Property Area, and categorical variables such as Education status and Employment Status.

Handling Missing Values

Null values in numerical columns are replaced with the mean, while categorical variables, Gender and Marital status were filled with the mode.

Encoding Categorical Variables

Categorical features, Gender and Education were converted into numerical values using Label Encoding or One-Hot Encoding to ensure compatibility with machine learning algorithms.

Normalization

Features were normalized using techniques like Standardization to maintain uniformity in the dataset.

Correlation Analysis:

A heatmap was generated to identify correlations between features. For example, Applicant Income and Loan Amount showed a positive correlation, while Loan Amount Term exhibited a negative correlation with other features.

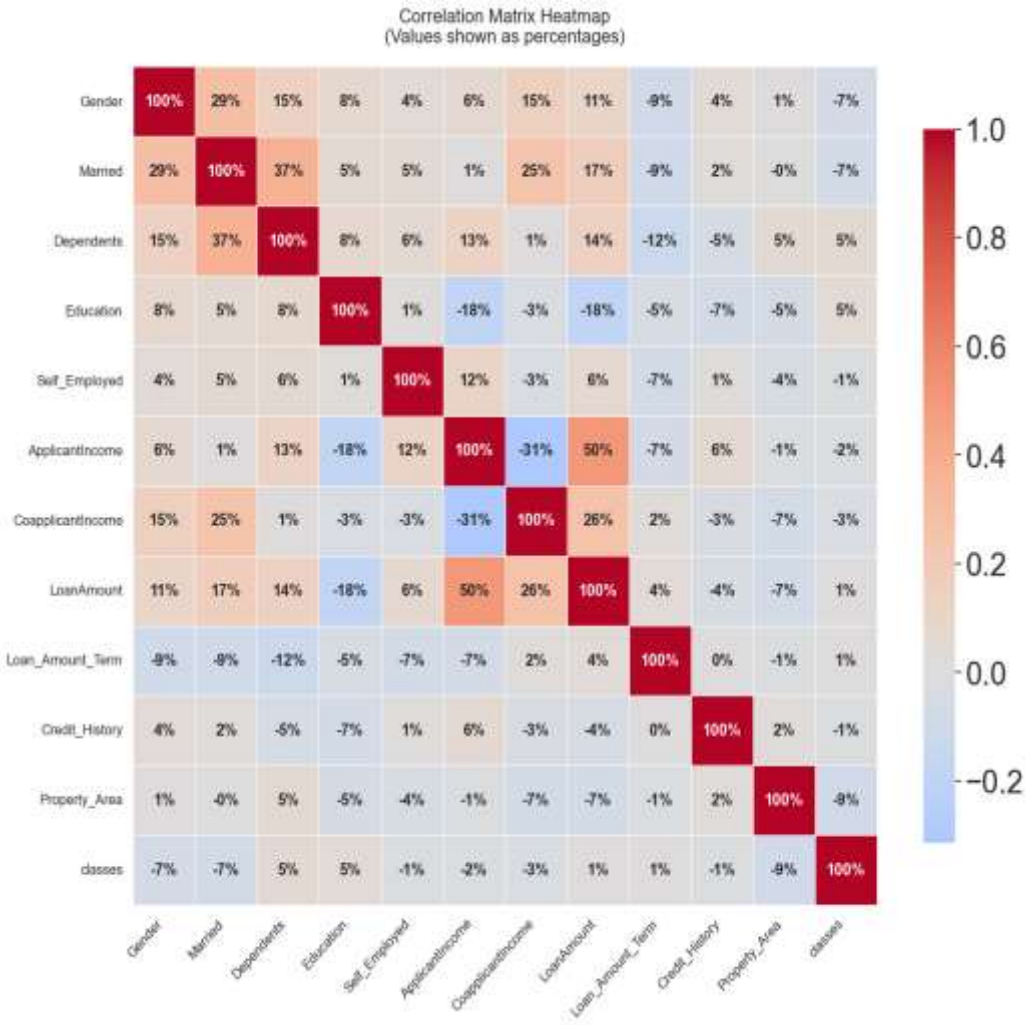

Figure 3.1 Correlation Analysis among features

Feature Importance

Chi-square technique was used to rank features based on their importance in predicting loan approval.

Model Selection and Training

We employed Supervised learning for the modeling. These include Artificial Neural Network, Decision Trees and Logistic Regression

Data Splitting

The dataset was split into training (70%) and testing (30%) sets using the split function from the Scikit-learn library.

Model Evaluation

Figure 3.2 shows the transition on the methods involved in this research

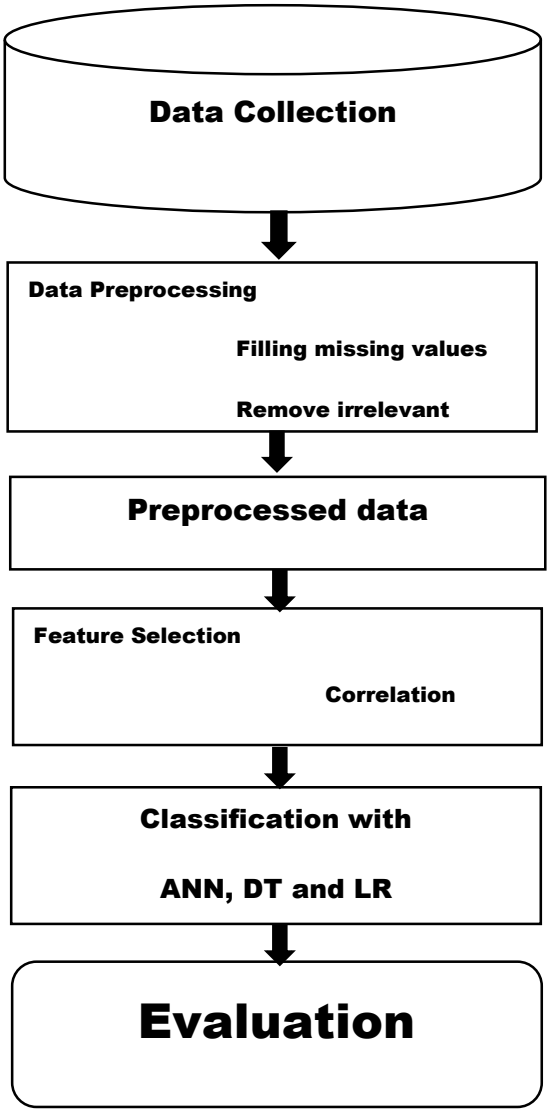

Figure 3.2 System Architecture

Evaluation Metrics

Performance was evaluated using sensitivity, specificity, accuracy, recall, and AUC curves.

Confusion Matrix

Provides insights into true positives, false positives, true negatives, and false negatives.

Comparative Analysis

The performance of each algorithm is compared to select the best model. For instance, Random Forest Model achieve the highest accuracy and this is chosen for deployment.

Web Application

The selected model is integrated into a web interface using Flask (Python backend) and HTML/CSS (frontend). Users input their details, and the system returns a loan approval/rejection result.

Results

The results from the experiment can be seen in tables and charts below

Feature Selection

Table 1: Table of Features, chi-Square and P-Values

S/N	Feature	Chi-Square	P-Value
1	Applicant Income	16903.1000	<0.0001
2	Co-applicant Income	775.3740	<0.0001
3	Loan Amount	67.8237	<0.0001

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S/N	Feature	Chi-Square	P-Value
4	Property Area	7.3472	0.0067
5	Dependents	4.7444	0.0294
6	Education	2.5531	0.1101
7	Married	2.3818	0.1228
8	Gender	1.1651	0.2804
9	Loan Amount Term	0.2050	0.6507
10	Self Employed	0.0582	0.8094
11	Credit History	0.0202	0.8871

Modeling Results

Table 2: Model Evaluation Metrics

MODELS	SENSITIVITY (%)	SPECIFICITY (%)	ACCURACY (%)	F1-SCORE (%)	AUC (%)
ANN	88.83	16.37	53.53	66.25	54.11
DT	68.88	96.46	82.23	80.00	82.67
LR	53.94	54.87	54.39	54.97	57.00
CHI-ANN	66.67	72.73	70.09	73.28	74.94
CHI-DT	80.39	83.33	82.05	83.97	83.20
CHI-LR	72.55	69.70	70.94	73.02	75.30

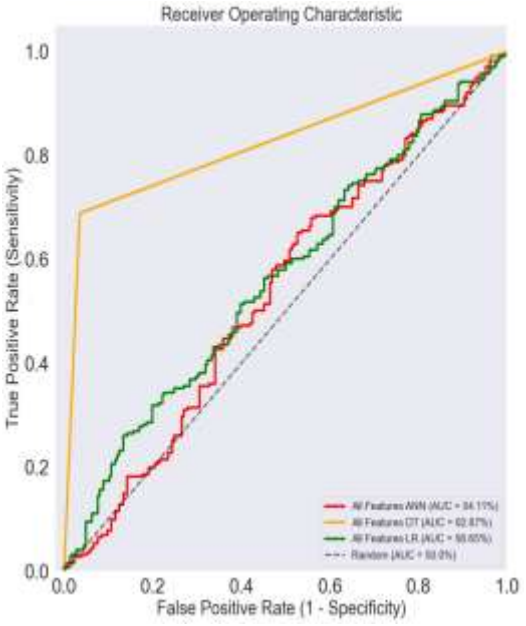

Figure 4.1 ROC of Models with All features

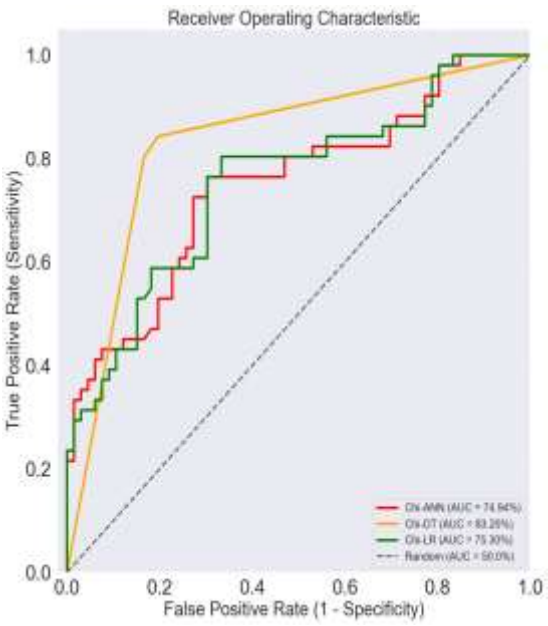

Figure 4.2 ROC of Models with Chi-Squared Selected features

Web Application

The model was deployed using a python Flask library in which the set of variables are entered and the prediction is done . the is embedded within a web application. Figure 4.3 shows the prediction interface of a mobile web

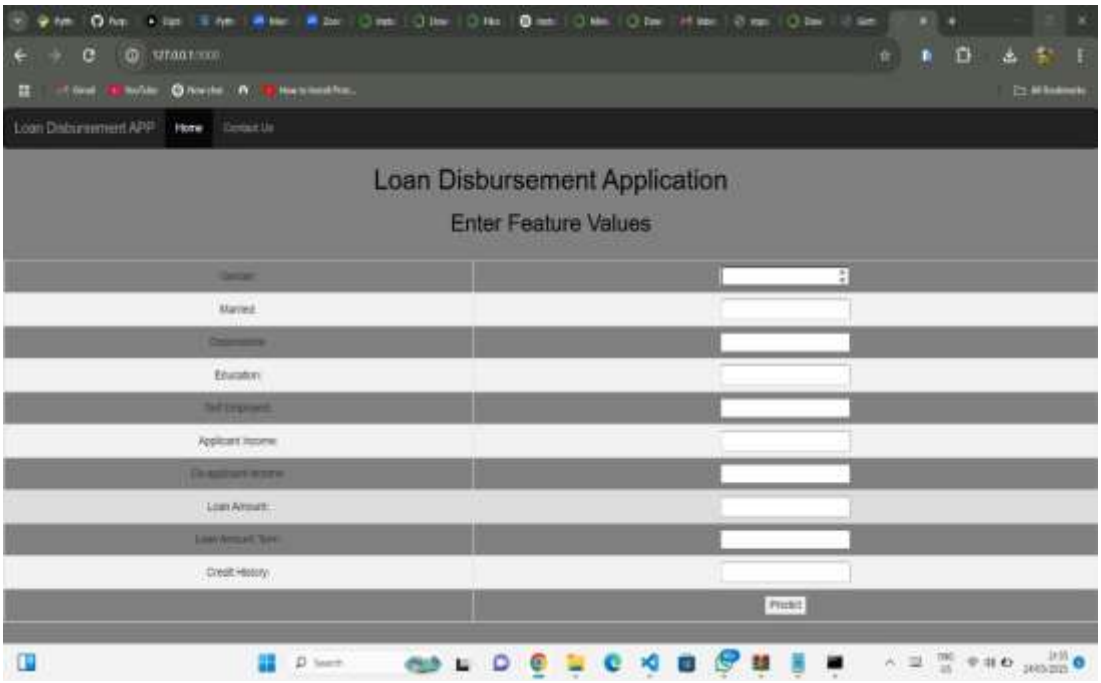

Figure 4.3: Web-Based Application of a Loan App – Input Page

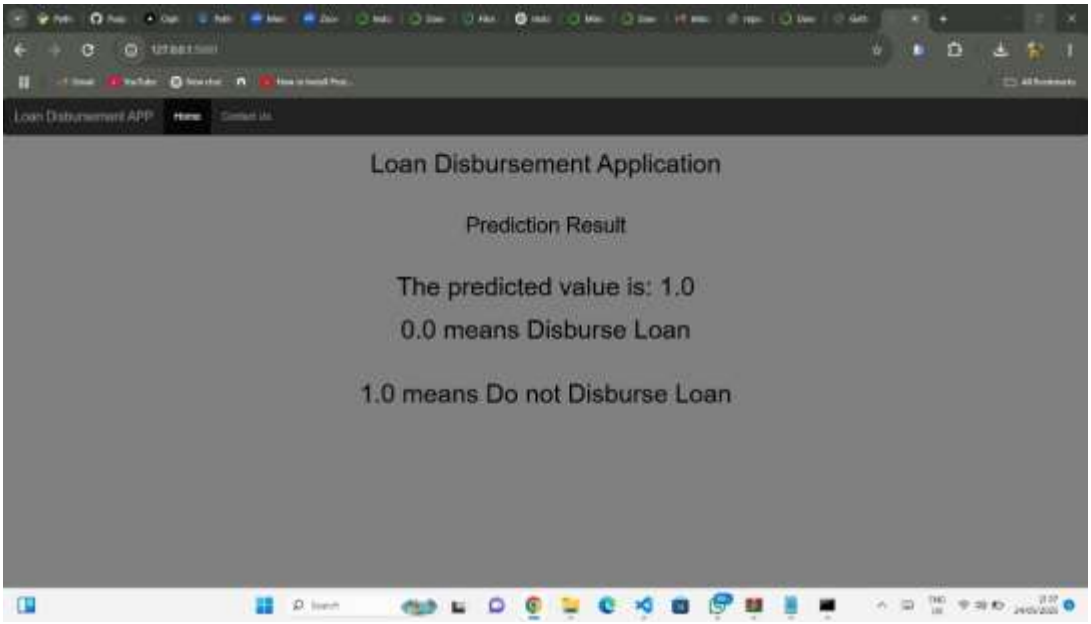

Figure 4.4: Web-Based Application of a Loan App – Output Page

Discussion

The aim of this research was to develop and application capable of predicting whether loan takers from a financial institution will repay or default. We achieved this aim by gathering a loan dataset containing 1,555 records from Kaggle, an online repository. We preprocessed this dataset by removing irrelevant features, encoding the numerical features, filling missing values, normalization. We split the dataset to 70:30 for training and testing respectively. We built 6 supervised machine learning models which are ANN, DT, LR and their Chi-Squared variants DT with Chi-squared selected features achieved the best metric with sensitivity of 80.39%, specificity of 83.33%, Accuracy of 82.05%, F1 Score of 83.97% and AUC of 83.20%. ANN showed a good sensitivity a poor specificity. While LR showed a random performing model. Our works compared with the works of [37] who got accuracy of 75.08%. Our works outperformed the model with 82.05% accuracy. The strength of our work lies in the Chi-Squared feature selection techniques which chose only important features for the computation. The selected features are Applicant Income, Co-applicant Income, Loan Amount, Property Area and Dependents. Naturally speaking, these features are considered to be important in loan disbursement. The limitation to our work is static model's decision over time since users behavior might change over time and lack of external validation of the model.

Conclusion

This research studied loan eligibility application development and our target was to develop and application that will allow loan eligibility to be predicted using loan borrower's information. We successfully developed a DT model which was eventually used to build a web-based application in the for predicting bank customer's eligibility at borrowing loans. Our results show that customers records can be used to predict customer's eligibility. Our model has a high predictive value and it can be trusted by financial institutions to disburse loan. We also identified that the most important factor to be considered before giving out loans are Applicant Income, Co-applicant Income, Loan Amount, Property Area, Dependents We would suggest a second layer confirmation if the institution is uncomformable of the user's information. This is a valuable information for financial institutions to adopt. This will prevent them from losing money to loan defaulters.

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