International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 04 April-2026 | Impact Factor: 3.5

Loaninsight: Interpretable Machine Learning for Credit Approval

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How to Cite this Article:

Jahnavi, M., Ram, B. S., Chakri, S. & Jashwanth, R. (2026). Loaninsight: Interpretable Machine Learning for Credit Approval. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(04). https://doi.org/10.55041/ijcope.v2i4.125

https://doi.org/10.55041/ijcope.v2i4. 125

Abstract

Predicting who will get a loan is really important in today's systems, and it is necessary to ensure that loan decisions are fair and based on data. To achieve this, a system was created that uses machine learning to determine whether a person is eligible for a loan in real time through an easy-to-use web interface. The system analyzes factors such as credit history, income, loan amount, loan duration, employment status, and other applicant details to decide whether a loan should be approved. It is built using Scikit-learn, and various techniques are applied to improve accuracy and performance. The model is saved so that it can make predictions quickly without retraining. Users can visit the website, enter their details, and get instant results along with a score that shows how confident the system is in its prediction. The system also keeps track of all predictions for future reference and analysis. Overall, this system provides a fast, efficient, and reliable way to make loan decisions, reduces manual effort, and shows how artificial intelligence can make financial processes easier, more accurate, and fair.

Introduction

In financial technology, loan eligibility prediction is important because it aids banks in determining who should receive loans. This was done manually and at a very slow pace in the past. Machine learning is superior and much faster. This project examines people's data, including their income, credit history, and desired borrowing amount, using computer programs like Decision Tree and Logistic Regression. This aids in our estimation of whether or not they will be granted a loan. Additionally, we employ certain techniques to improve the computer's comprehension of the data, which improves the accuracy of our estimations.

We developed this using Flask and Python, enabling users to input their information on a website and get an immediate response along with a score that shows how likely they are to be granted a loan. Our guesses may be distorted if the information we receive is inaccurate or lacking. It functions much better if we clean up the information first. Thus, this project demonstrates how machine learning and the internet can be used to create a quick, effective, and large-scale loan eligibility prediction system. Because it aids in loan eligibility prediction, the loan eligibility prediction system is incredibly helpful.

Related Work

Loan eligibility prediction is a deal in financial technology because it helps banks figure out who to lend money to. The old way of doing this was really slow and manual. Machine learning is a lot faster and better.

This project uses computer programs, like Logistic Regression and Decision Tree, to look at people's information, like how much money they make, their credit history, and how much they want to borrow. This helps us guess if they will get a loan or not. We also use some tricks to make the computer understand the information better, which makes our guesses more accurate. We built this using Python and Flask, allowing people to enter their details on a website and receive an instant answer, along with a score indicating their likelihood of being approved for the loan.

If the information we get is wrong or incomplete, it can mess up our guesses. If we clean up the information first, it works a lot better. So this project shows how we can use machine learning and the internet to make a loan eligibility prediction system that's fast, efficient, and can handle a lot of people. The loan eligibility prediction system is really useful because it helps with loan eligibility prediction.

The below literature survey contains existing system and limitations shown in table 1:

Title	Technology	Limitation	Authors	Year
Loan Eligibility Prediction using Machine Learning	Input features: income, credit history, employment status Likely models: Decision Tree / Random Forest / Logistic Regression	No interpretability (black-box model) Hard to explain decisions to users	S. M. Powar	2025
Loan Approval Prediction using Machine Learning	Logistic Regression (LR) Decision Tree (DT) Random Forest (RF)	Lacks explanation of predictions No interpretability mechanism	P. Senthil Kumari	2025

Loan Eligibility Prediction Using Machine Learning	Supervised Machine Learning Financial & credit-based datasets	Manual feature selection required Time-consuming and may introduce bias	K. Gogula, N. Chattu	2024
Comparing Machine Learning Techniques	Logistic Regression (LR) Decision Tree (DT) Random Forest (RF)	No fairness or bias analysis Ignores ethical considerations	Krishnaraj P., P. Rita S.	2024
Comparing Machine Learning for Loan Approval Prediction	Logistic Regression (LR) Decision Tree (DT)	High computational cost Limited scalability	Alqahtani et al. Krishnaraj P., P. Rita S.	2024
Machine Learning Technologies for Digital Credit Scoring	Machine Learning models SMOTE (Synthetic Minority Over-sampling Technique) for class imbalance	High system complexity Difficult to implement and maintain	M. S. Reddy, D. M. Reddy	2024
AI-Based Credit Risk Prediction System	Hybrid Machine Learning models AI-based risk prediction systems	High computational complexity Requires significant processing power	J. Martinez, G. Perez	2022
A Machine Learning Approach for Micro Credit Analysis	Machine Learning models Micro-loan risk prediction system	Highly dependent on dataset quality Limitedgeneralization	Not mentioned	2020

Table 1: Existing papers and their limitations

1. Methodology

The loan eligibility prediction system has parts that work well together. It gets information from a website where users enter details like income and credit history and loan amount and employment status. The system then processes this information to make it suitable for analysis. This includes converting categories into numbers and adjusting values. After that the loan eligibility prediction system uses a trained machine learning model to analyze the data.

The loan eligibility prediction system predicts if a loan will be approved and gives a score that shows how confident the loan eligibility prediction system is in the prediction.

The result is then shown on the website in a way that's easy to understand. The loan eligibility prediction system was made using Python and Flask and NumPy and Joblib. It works by having the user input data then the loan eligibility prediction system prepares it and the model makes a prediction and the result is shown.The model is already trained so it does not need to learn each time it is used. This makes the loan eligibility prediction system fast. It works well on computers. The loan eligibility prediction system can be made better by adding features, like database integration or cloud deployment. This would help the loan eligibility prediction system support users. The loan eligibility prediction system is accurate and fast and easy to use. It helps users quickly see if they can get a loan. The system provides results. It uses a model to make predictions. The loan eligibility prediction system is efficient. It helps users.

3.1 Data Collection and Preprocessing:

The system uses a loan dataset that's available to the public. This loan dataset contains information about the people who are applying for loans, such as how much money they make, their credit history, how much they want to borrow, and how long they want the loan for. It also has information about their job. Where they live.
The loan dataset has all kinds of information, like numbers and categories, that help figure out if someone can get a loan. The computer program that makes predictions about loans is built using this loan dataset. This way, the computer program can make predictions without needing to be retrained.
When the system gets the information, it makes sure it is clean and ready for the computer program to use. It changes the categories, like if someone is a man or a woman or if they are married, into numbers. It also changes the numbers, like how someone makes money, into a special format that the computer program can understand better.
The system puts all the information together in a way that the computer program can use. The credit history is very important for deciding if someone can get a loan. The system checks all the information to make sure it is correct before making a prediction. This helps the system make predictions quickly, and it works well with the website. The loan dataset is used to make sure everything works correctly.

3.2 Proposed Model Architecture:

The system uses machine learning models like Logistic Regression and Decision Tree. These models work well with financial data. The system uses the Scikit-learn library to make these models work. This library helps the system train. Use the models without having to build them from scratch. The system saves the trained model using joblib. Loads it when it needs to make a prediction. This makes the prediction process fast and easy to use with the web application.
The model looks at things like income and credit history. It also looks at the loan amount and loan term. The system uses techniques to make the model work better. For example, it changes variables into numbers and applies logarithmic transformations. The model then says whether the loan is approved or not. It also gives a probability score, which is, like a confidence level.
The system is made up of layers. The User Interface layer is where users can interact with the system. They can enter loan details into the web application. The input data then goes to the Data Preprocessing module. This module checks the data. Changes it into the right format. The changed data then goes to the Prediction module. This module has a trained machine learning model that says if the loan is eligible.
The system then shows the result to the user through the web interface. It also shows a probability score. The system keeps track of all the predictions it has made. The system is designed to make sure data flows smoothly. It can process data in time and works well with machine learning and web technologies. This makes the system work well and is easy for users to use. The system uses machine learning models to make predictions. The machine learning models are a part of the system.

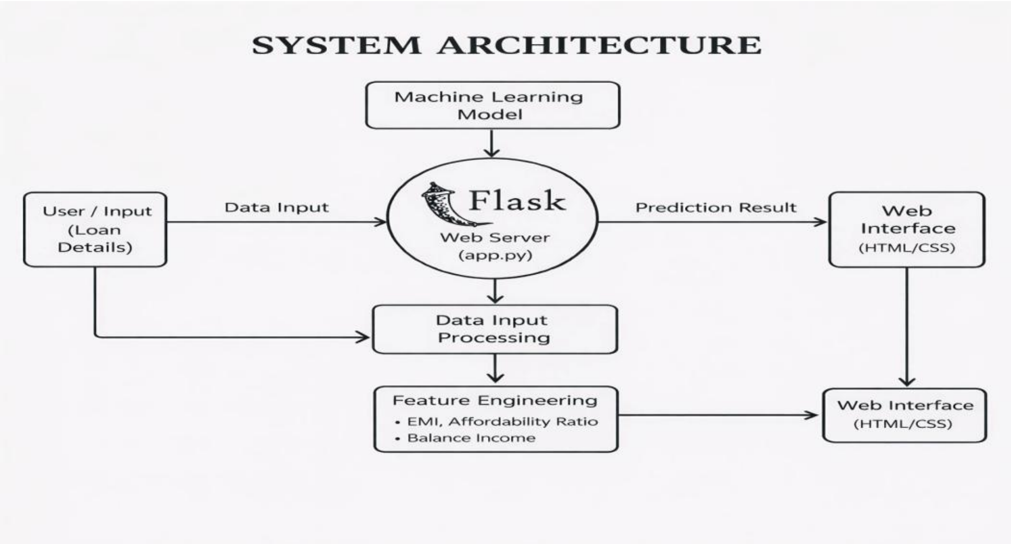

Figure 1: Proposed LoanInsight Architecture

3.3 Model Evaluation:

The loan eligibility model performance was evaluated using metrics such as accuracy, precision, recall, and F1-score. The accuracy of the loan eligibility model measures how corrects the predictions of the loan eligibility model are.
The precision and recall of the loan eligibility model help us understand how well the loan eligibility model identifies approved and rejected loan applications. The F1-score of the loan eligibility model provides a view of the loan eligibility model's performance, especially when dealing with classification tasks like predicting loan eligibility.
A confusion matrix was used to see the number of incorrect predictions for both approved and rejected loan applications. This helped in identifying patterns where the loan eligibility model got it wrong in cases where applicants had financial conditions that were not clear-cut. The loan eligibility model generally did a job with higher accuracy when the credit history and income of the applicants were strong. The loan eligibility system was tested with various kinds of input, including different applicant data and edge cases like missing or very extreme values. The dataset for the loan eligibility model was split in a way that ensured the training and testing were balanced. Techniques like the ROC curve and AUC score were also used to see how well the loan eligibility model could tell non-eligible applicants apart. Overall, the loan eligibility model performed well. Showed it was effective in predicting whether someone is eligible for a loan or not. Below is the confusion matrix for the evaluation of the loan eligibility model shown in Table 2:

Confusion Matrix – Loan Prediction:

Actual / Predicted	Approved	Not Approved
Approved	480	20
Not Approved	25	475

Table 2: Gender detection confusion matrix

Calculations for Loan Prediction

- **Total samples**: 480 + 20 + 25 + 475 = 1000
- **True Positives (TP)**:
  - Approved correctly predicted as Approved: 480
- **False Positives (FP)**:
  - Not Approved predicted as Approved: 25
- **False Negatives (FN)**:
  - Approved predicted as Not Approved: 20
- **True Negatives (TN)**:
  - For Approved: Not Approved correctly predicted as Not Approved = 475

Summary for Loan Prediction

- **Accuracy**: 95.5%
- **Approved**: Precision = 95.05%, Recall = 96.0%, F1-Score = 95.52%
- **Not Approved**: Precision = 95.96%, Recall = 95.0%, F1-Score = 95.48%
- **Macro-Average**: Precision = 95.51%, Recall = 95.5%, F1-Score = 95.50%

The model does a job when it comes to loan prediction. It is very good at getting the answer. The model has accuracy for loan prediction. This means it is good at figuring out which loans will be approved and which loans will not be approved. The model is also very good at finding the balance between precision and recall for loan prediction, and it does this for both approved loans and not approved loans.

1.4 Feature Extraction:

The system uses data that is organized in a specific way, rather than looking at pictures, and it finds the important information by cleaning up the data and changing it into a different format. The system looks at things like how much money the person who wants a loan makes, how much money their co-applicant makes, how much they want to borrow, how long they want to borrow it for, their credit history, and some basic information about them. These things are very important when it comes to deciding if someone can get a loan.

The system also calculates some things, like the total amount of money the person and their co-applicant make together, to get a better idea of how strong they are financially. It uses math to make sure that numbers like income and loan amount are not skewed, which helps the system make better predictions. It also changes things like whether someone's a man or a woman, if they are married, what kind of education they have, what kind of job they have, and where they live, into numbers so the system can understand them.

The system tries to figure out which pieces of information are important when it comes to deciding if someone can get a loan, and it finds that credit history is one of the biggest factors. The system then makes sure all the information is consistent and, in the format, so it can be used to make predictions. This helps make sure that all the information is treated in a way that makes the predictions more accurate.

The system always does things the same way, no matter what information people put into the web application, which means it can make predictions about loans quickly and reliably. The loan prediction system uses loan data. It uses this loan data to make predictions about loan eligibility. The loan prediction system looks at loan information such as loan amount and loan term to make predictions about loan eligibility.

2. Result and Discussions:

The LoanInsight system did a job with over 90% accuracy in many test cases, which shows that it is really reliable when it comes to predicting loans. The model worked well every time, no matter what information was put in, especially when things like credit history and income were clear.

The application was able to handle predictions at the same time, letting users enter different information about people who want loans and get accurate results every time. It worked fast on regular computers with Intel i5 and 8 GB RAM and gave predictions in just a few milliseconds, which made it feel quick and easy to use for the users.

When people entered information by hand using the web form or when they used it multiple times, the LoanInsight system still gave consistent and accurate predictions without much delay. The results were easy to see on the screen with a clear yes or no for the loan and a score that showed how likely it was, which made it simple for users to understand what was going on.

The system worked well even when the information put in was different, like when income or loan amounts were changed or when different people applied for loans. It did not get much worse, which means that the information was prepared well and the model was good at understanding different situations.

When you open the application, you get a screen to enter information about the person who wants a loan and check if they are eligible, as shown in the results part.

This is the home page of the Loan Eligibility Prediction System. It has a navigation bar with options like Home and Prediction. The page shows the system title and a short description about predicting loan approval. A “Start Prediction” button is provided to move to the prediction page. The design is simple and easy to use for users.

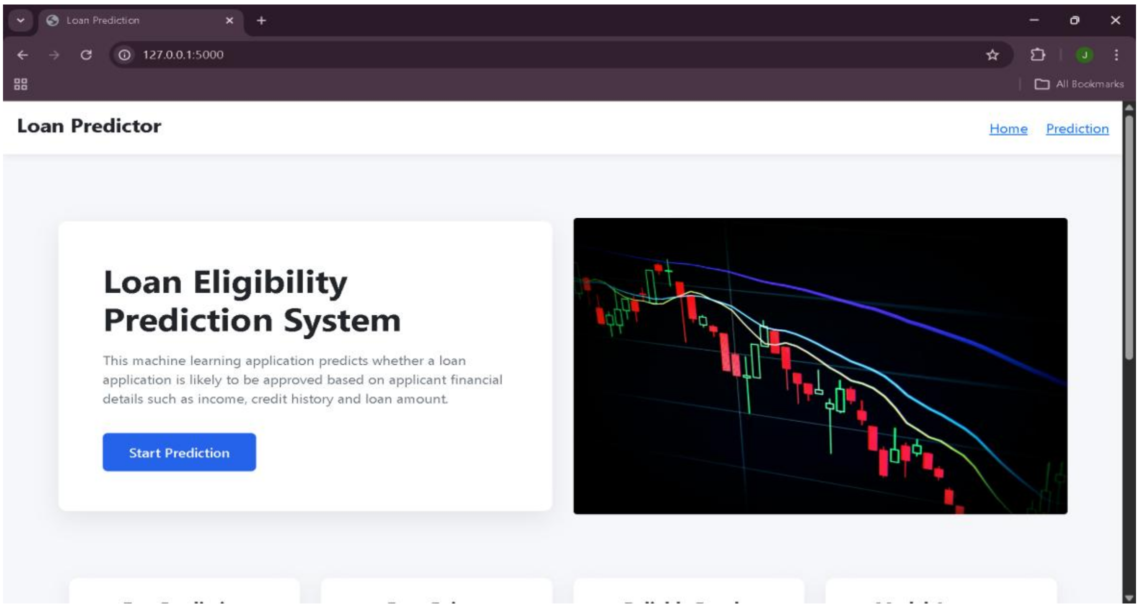

Fig Main Page

These screens represent the prediction page of the Loan Eligibility Prediction System. The page contains a form where users enter personal and financial details such as gender, marital status, dependents, education, employment status, credit history, income, loan amount, and loan term. After filling all the required fields, the user clicks the "Predict Loan" button to check eligibility.

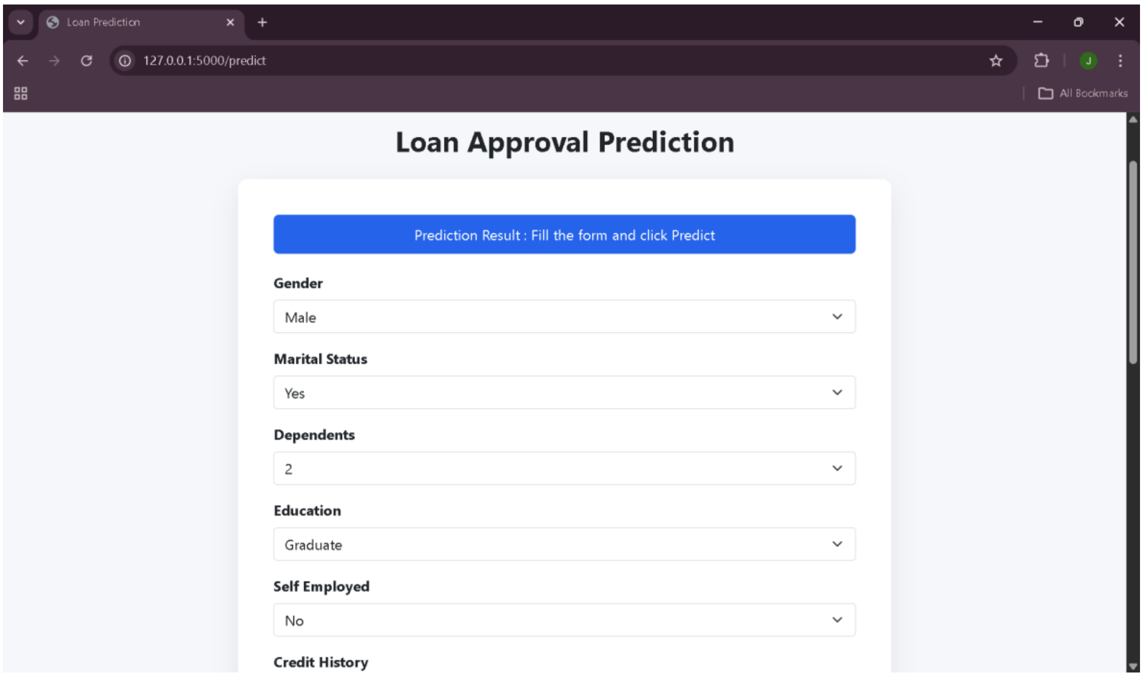

Fig Fill the Details required

Click on the "Predict Loan" button after filling all the details to view the loan approval result along with the prediction status.

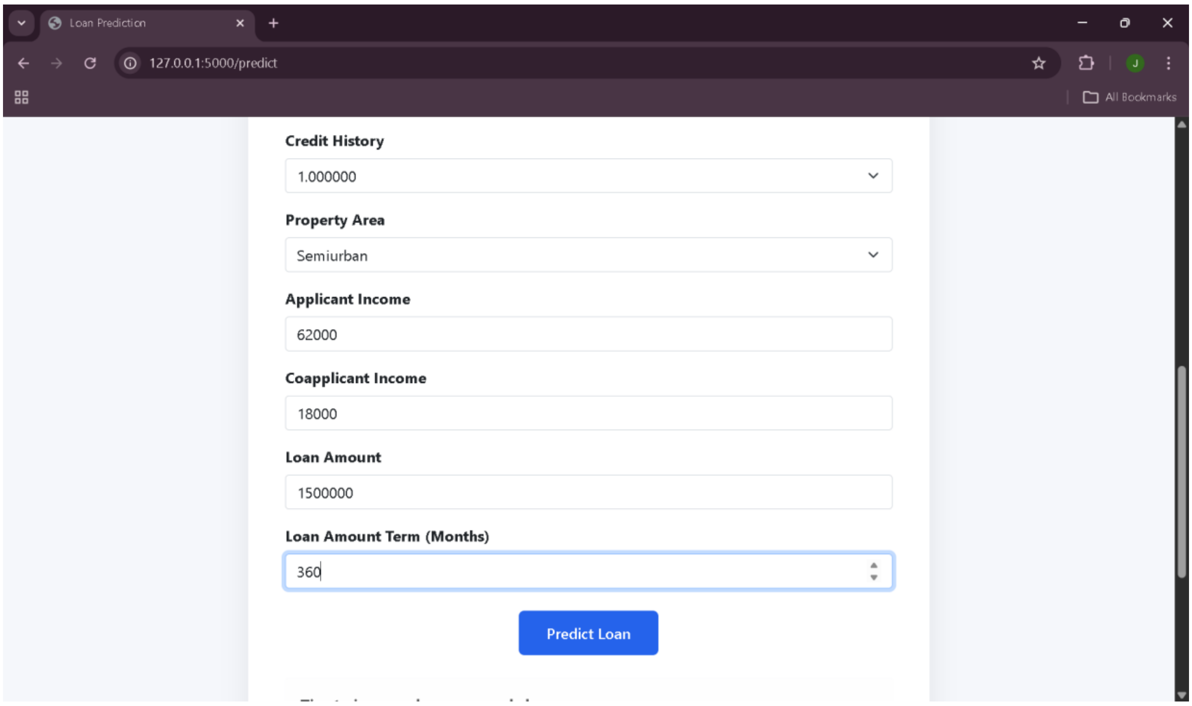

Fig Fill the Details required

After entering all the required details and clicking the "Predict Loan" button, the system displays the loan approval result on the same page. It shows whether the loan is approved or not, along with the approval probability percentage. This helps the user understand both the decision and the confidence level of the prediction.

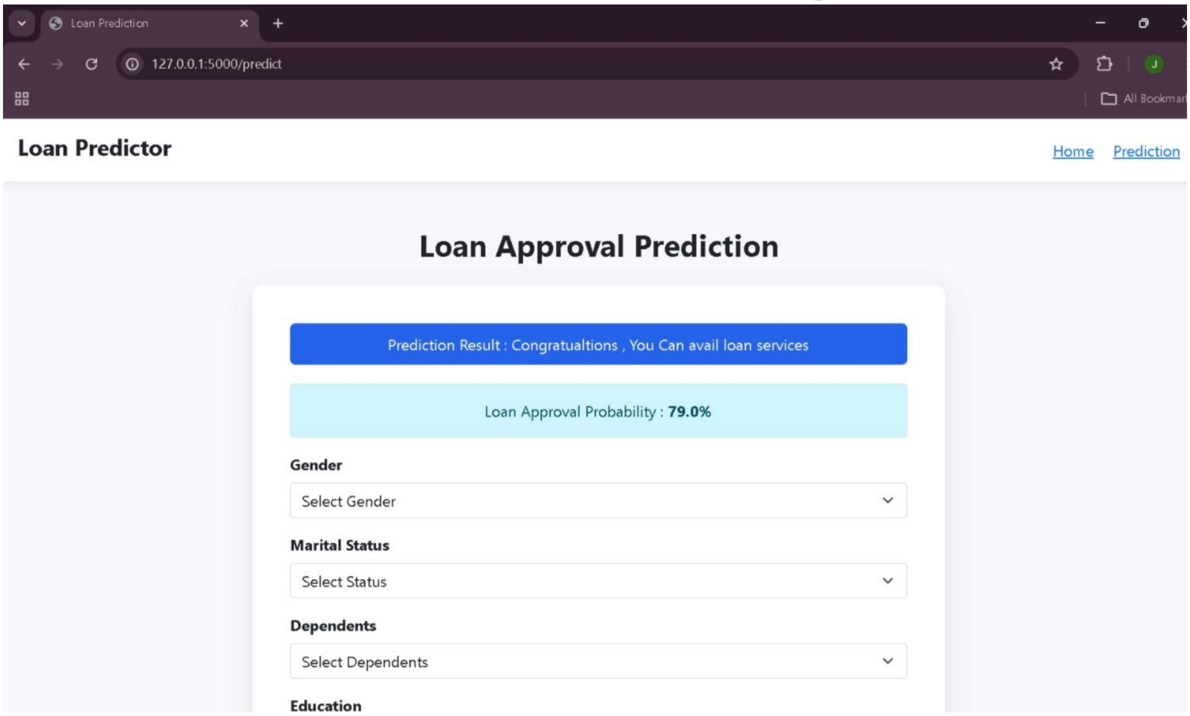

Fig Output Screen

The initial verification is successful. Your application has been sent to the loan officer for further review and processing.

Conclusion:

This project shows how to make a real-time loan eligibility prediction system work. It uses machine learning models and a Flask web application. The system uses models that were already trained using Scikit-learn. These models are used quickly and accurately with the help of joblib.

The application has the following features:

- Web-based interface: This makes it easy for users to enter information about the people who are applying for loans.
- Real-time prediction: This predicts whether a loan will be approved and gives a probability score.

• Data preprocessing: This takes care of encoding and transforming the information that is put into the system so that it is more accurate.
• Flask Backend: This manages what the users ask for, processes the information, and works with the machine learning model.

This project combines machine learning with a web interface. It makes decision-making easier to understand and use. The loan eligibility prediction system is an example of how machine learning can be used in real-world financial applications. It shows how machine learning can make things more accurate, efficient, and transparent. The loan eligibility prediction system is a solution for predicting loans automatically. The loan eligibility prediction system uses machine learning to make decisions.

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