केन्द्रीय प्रौद्योगिकी संस्थान कोकराझार
CENTRAL INSTITUTE OF TECHNOLOGY KOKRAJHAR
DEEMED TO BE UNIVERSITY UNDER MOE, GOVT. OF INDIA

Mini Project

Loan Default Prediction

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Introduction

“Loan default prediction” using machine learning is crucial for financial institutions to assess credit risk and optimize lending decisions. This project aims to develop a predictive model that can forecast whether a borrower is likely to default on a loan based on historical data and key features. By leveraging advanced analytics, we seek to enhance risk management practices and improve loan approval processes.

PROBLEM STATEMENT

- Time-Consuming Manual Process
- Inefficiencies and Delays
- Lack of Real-Time Responses
- Slower and Less Accurate Decisions

SOLUTION

- Implement Automated Loan Default Assessment
- Utilize Predictive Modeling
- Real-Time Decision Making
- Continuous Monitoring and Model Updating

Methodolgy

Loan Data (Input Data)

Data Preprocessing

Machine Learning Model Training

Model Evaluation

Deployment

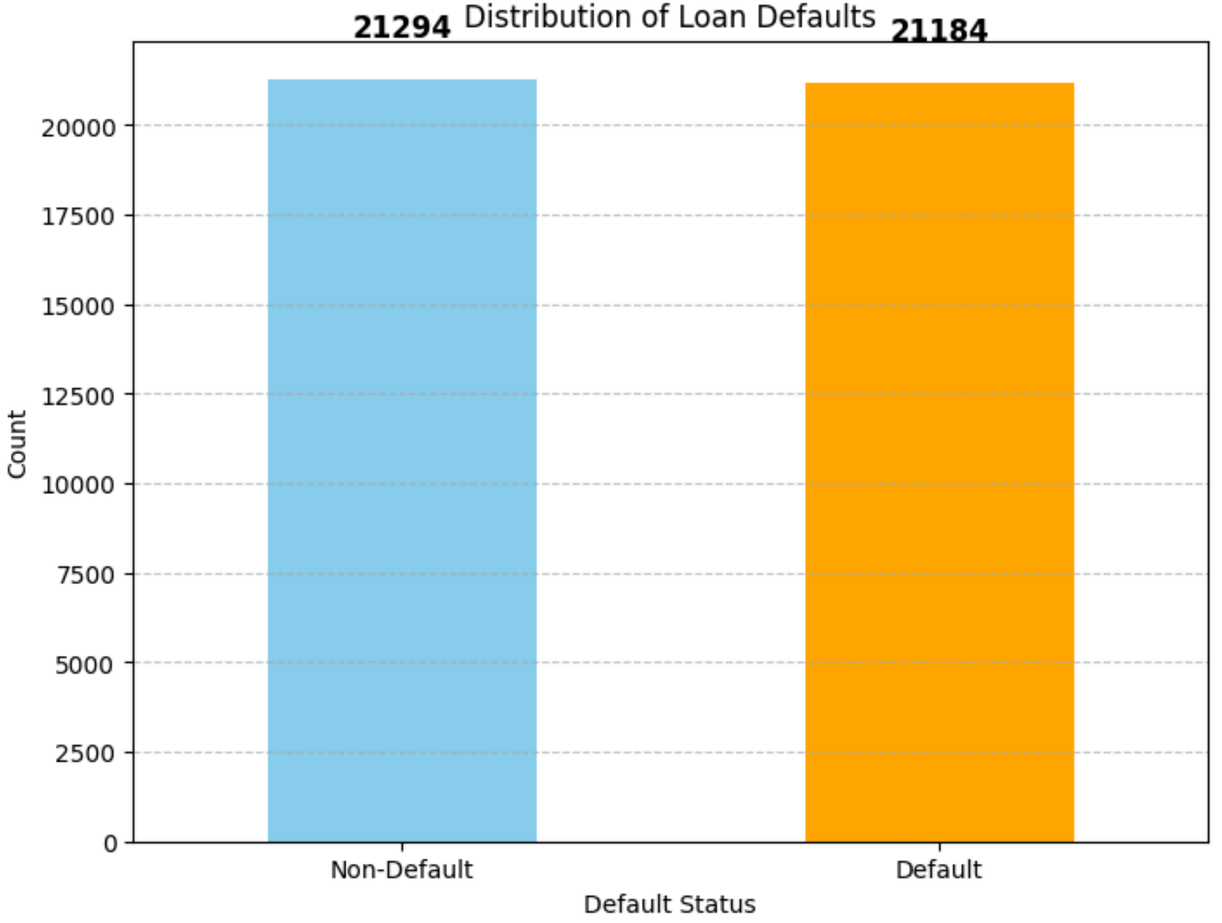
Loan Default Prediction

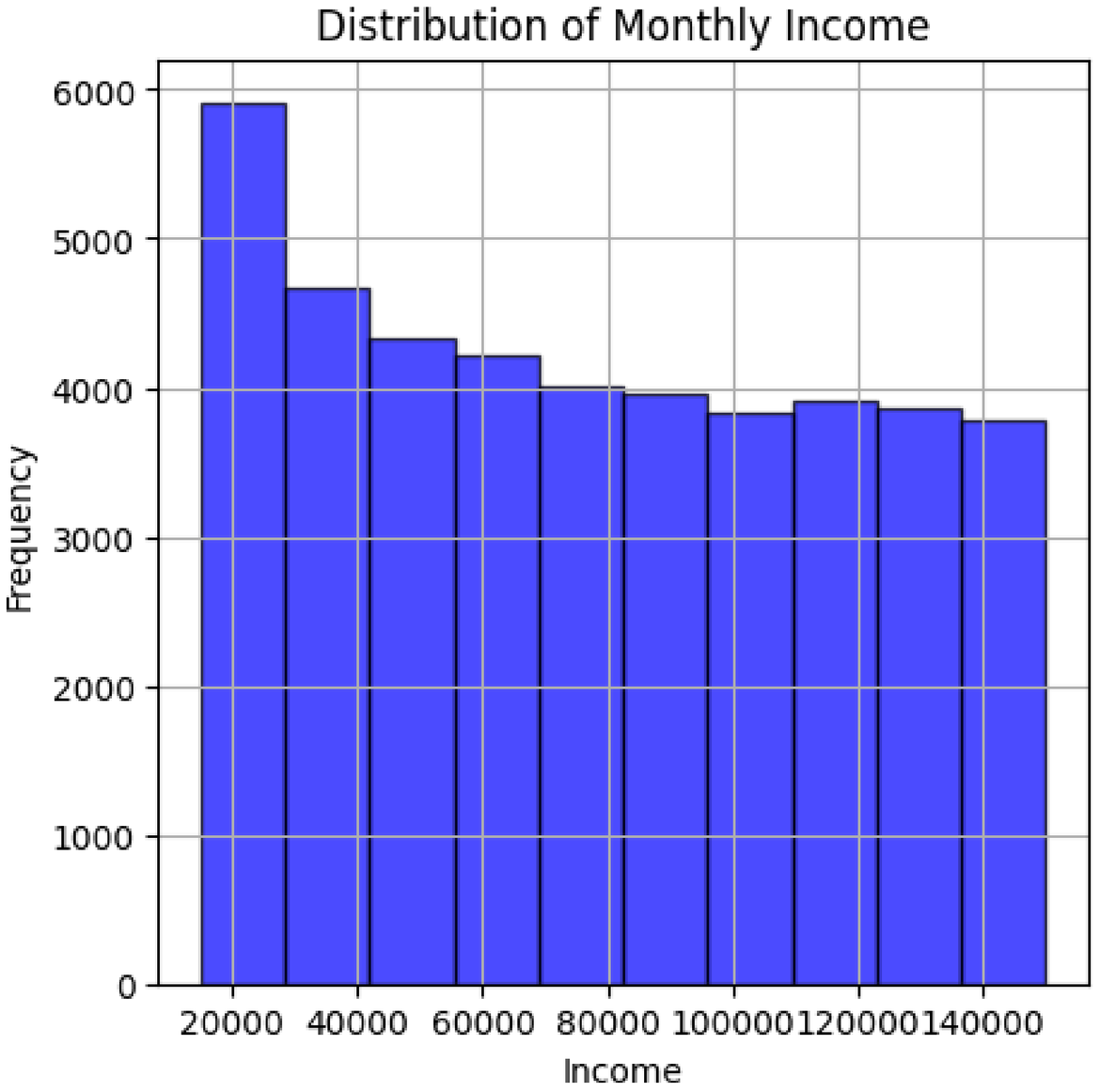
Output

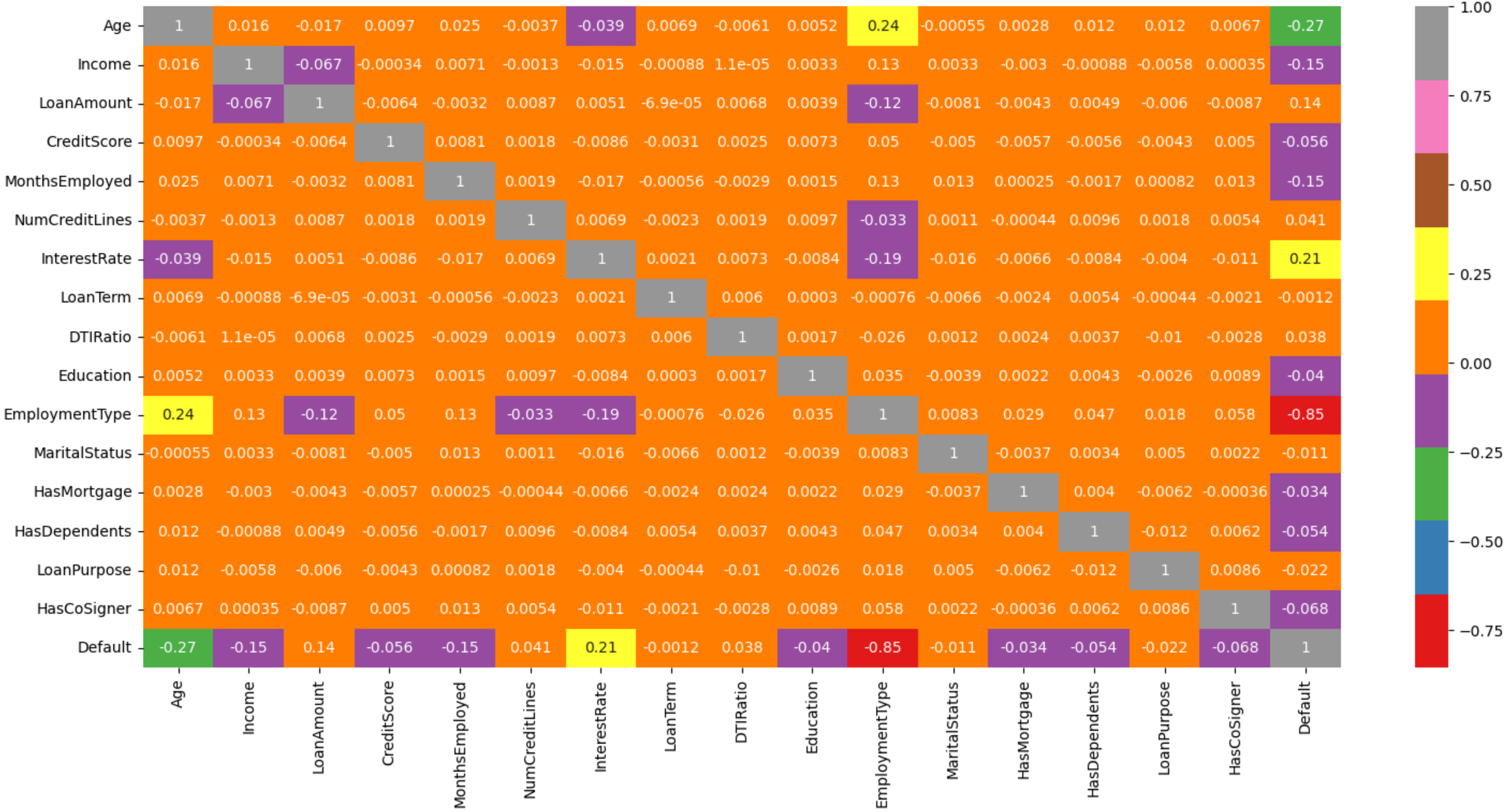
Data

- Age
- Income
- LoanAmount
- Credit Score
- Months Employed
- NumCreditLines
- Interest Rate
- Loan Term
- DTI Ratio
- Education
- Employment Type
- MaritalStatus
- Has Mortgage
- Has Dependents
- Loan Purpose
- Has Co Signer
- Loan Default

		Age	Income	LoanAmou	CreditScor	MonthsEm	NumCredit	InterestRa	LoanTerm	DTIRatio	Education	Employme	MaritalSta	HasMortga	HasDepen	LoanPurpc	HasCoSign	Default
21184	ZZY5HORA	22	123437	9163	582	108	1	8.39	36	0.69	PhD	Unemploy	Single	No	Yes	Education	No	0
21185	ZZZDJ23OK	30	118720	93079	619	51	1	5.41	60	0.65	High Schoc	Unemploy	Married	No	Yes	Other	No	0
21186	002EJYQA(	39	61393	167431	841	68	4	8.93	60	0.26	Master's	Full-time	Married	No	No	Education	No	1
21187	0042NIHB	24	95283	159587	539	50	4	20.61	36	0.63	Master's	Full-time	Divorced	No	Yes	Business	Yes	1
21188	004WNVB	52	111151	191688	843	54	4	23.93	12	0.27	High Schoc	Full-time	Married	No	Yes	Other	No	1
21189	00DWW2X	25	90046	155267	367	8	4	24.39	12	0.48	PhD	Full-time	Single	No	No	Education	No	1
21190	00W5DU2	23	124025	31936	664	44	2	24.61	48	0.52	Master's	Full-time	Divorced	No	No	Education	No	1
21191	013DGAEB	34	19665	126745	541	55	1	17.36	12	0.77	PhD	Full-time	Divorced	Yes	No	Business	Yes	1
21192	01HCWM6	36	35479	193321	489	14	1	17.92	48	0.15	High Schoc	Full-time	Single	No	Yes	Auto	No	1
21193	01LTICCI6'	32	18684	67703	743	61	4	3.07	48	0.11	Master's	Full-time	Divorced	Yes	Yes	Home	Yes	1
21194	01YOH9E9	50	129370	232769	810	16	3	11.37	48	0.11	High Schoc	Full-time	Married	No	Yes	Auto	Yes	1
21195	02D4E6RR	40	122111	178171	705	97	1	24.63	36	0.33	High Schoc	Full-time	Divorced	Yes	No	Business	No	1
21196	02GDBSIJD	47	38647	63255	449	5	3	20.13	24	0.29	PhD	Full-time	Divorced	Yes	Yes	Other	No	1
21197	02IKVK76V	23	22161	127466	753	103	3	17.45	12	0.54	PhD	Full-time	Married	Yes	Yes	Other	Yes	1
21198	02MA61ET	55	97676	157845	558	107	3	13.47	36	0.28	PhD	Full-time	Married	No	Yes	Education	Yes	1
21199	03IO75CAI	36	18586	97436	512	102	1	2.01	36	0.71	High Schoc	Full-time	Married	Yes	No	Business	No	1
21200	03L2IR9QT	58	36191	131550	736	7	2	23.25	60	0.64	PhD	Full-time	Single	Yes	No	Other	Yes	1
21201	03NS8IFYC	27	43996	166090	417	25	2	18.15	60	0.24	Master's	Full-time	Married	No	Yes	Auto	No	1


Distribution of Loan Defaults
21294
21184
Count
Default Status
Non-Default
Default
0
2500
5000
7500
10000
12500
15000
17500
20000


Distribution of Monthly Income
Frequency
Income
0
1000
2000
3000
4000
5000
6000
20000
40000
60000
80000
100000
120000
140000

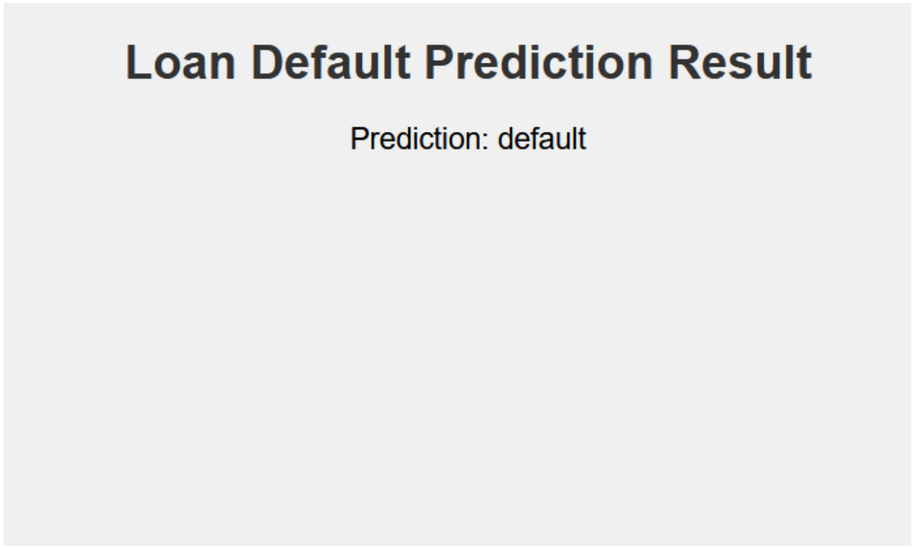

Age 1 0.016 -0.017 0.0097 0.025 -0.0037 -0.039 0.0069 -0.0061 0.0052 0.24 -0.00055 0.0028 0.012 0.012 0.0067 -0.27
Income 0.016 1 -0.067 -0.00034 0.0071 -0.0013 -0.015 -0.00088 1.1e-05 0.0033 0.13 0.0033 -0.003 -0.00088 -0.0058 0.00035 -0.15
LoanAmount -0.017 -0.067 1 -0.0064 -0.0032 0.0087 0.0051 -6.9e-05 0.0068 0.0039 -0.12 -0.0081 -0.0043 0.0049 -0.006 -0.0087 0.14
CreditScore 0.0097 -0.00034 -0.0064 1 0.0081 0.0018 -0.0086 -0.0031 0.0025 0.0073 0.05 -0.005 -0.0057 -0.0056 -0.0043 0.005 -0.056
MonthsEmployed 0.025 0.0071 -0.0032 0.0081 1 0.0019 -0.017 -0.00056 -0.0029 0.0015 0.13 0.013 0.00025 -0.0017 0.00082 0.013 -0.15
NumCreditLines -0.0037 -0.0013 0.0087 0.0018 0.0019 1 0.0069 -0.0023 0.0019 0.0097 -0.033 0.0011 -0.00044 0.0096 0.0018 0.0054 0.041
InterestRate -0.039 -0.015 0.0051 -0.0086 -0.017 0.0069 1 0.0021 0.0073 -0.0084 -0.19 -0.016 -0.0066 -0.0084 -0.004 -0.011 0.21
LoanTerm 0.0069 -0.00088 -6.9e-05 -0.0031 -0.00056 -0.0023 0.0021 1 0.006 0.0003 -0.00076 -0.0066 -0.0024 0.0054 -0.00044 -0.0021 -0.0012
DTIRatio -0.0061 1.1e-05 0.0068 0.0025 -0.0029 0.0019 0.0073 0.006 1 0.0017 -0.026 0.0012 0.0024 0.0037 -0.01 -0.0028 0.038
Education 0.0052 0.0033 0.0039 0.0073 0.0015 0.0097 -0.0084 0.0003 0.0017 1 0.035 -0.0039 0.0022 0.0043 -0.0026 0.0089 -0.04
EmploymentType 0.24 0.13 -0.12 0.05 0.13 -0.033 -0.19 -0.00076 -0.026 0.035 1 0.0083 0.029 0.047 0.018 0.058 -0.85
MaritalStatus -0.00055 0.0033 -0.0081 -0.005 0.013 0.0011 -0.016 -0.0066 0.0012 -0.0039 0.0083 1 -0.0037 0.0034 0.005 0.0022 -0.011
HasMortgage 0.0028 -0.003 -0.0043 -0.0057 0.00025 -0.00044 -0.0066 -0.0024 0.0024 0.0022 0.029 -0.0037 1 0.004 -0.0062 -0.00036 -0.034
HasDependents 0.012 -0.00088 0.0049 -0.0056 -0.0017 0.0096 -0.0084 0.0054 0.0037 0.0043 0.047 0.0034 0.004 1 -0.012 0.0062 -0.054
LoanPurpose 0.012 -0.0058 -0.006 -0.0043 0.00082 0.0018 -0.004 -0.00044 -0.01 -0.0026 0.018 0.005 -0.0062 -0.012 1 0.0086 -0.022
HasCoSigner 0.0067 0.00035 -0.0087 0.005 0.013 0.0054 -0.011 -0.0021 -0.0028 0.0089 0.058 0.0022 -0.00036 0.0062 0.0086 1 -0.068
Default -0.27 -0.15 0.14 -0.056 -0.15 0.041 0.21 -0.0012 0.038 -0.04 -0.85 -0.011 -0.034 -0.054 -0.022 -0.068 1
Age
Income
LoanAmount
CreditScore
MonthsEmployed
NumCreditLines
InterestRate
LoanTerm
DTIRatio
Education
EmploymentType
MaritalStatus
HasMortgage
HasDependents
LoanPurpose
HasCoSigner
Default
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

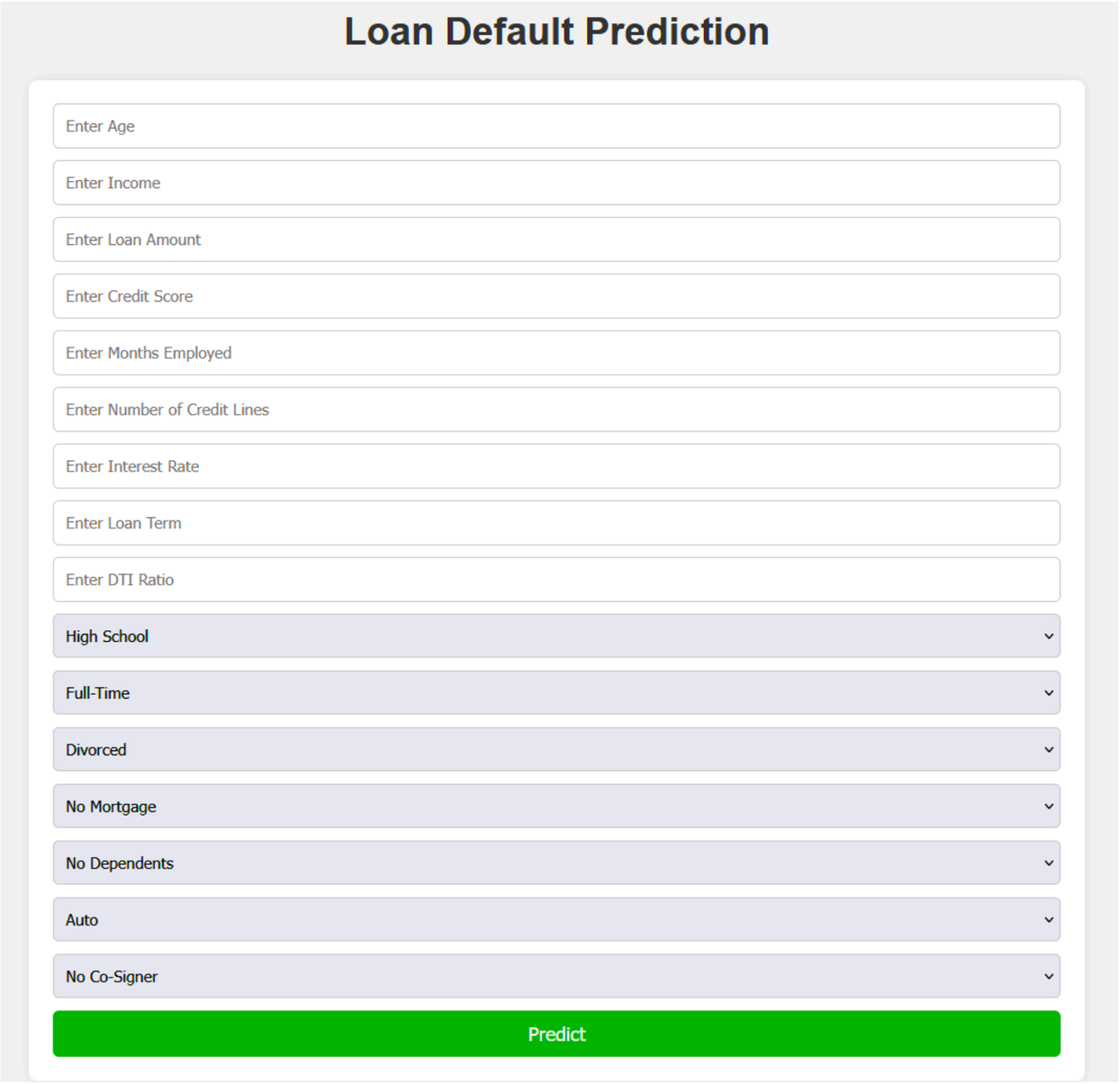
Machine Learning Models

models	accuracy
RandomForestClassifier	0.99
XGBClassifier	0.99
KNeighborsClassifier	0.92
GaussianNB	0.80
LogisticRegression	0.69

Result

exported model: Random forest





Loan Default Prediction

30

118720

93079

619

51

1

5.41

60

0.65

High School

Unemployed

Married

No Mortgage

Has Dependents

Other

No Co-Signer

Predict

Loan Default Prediction

39

61393

167431

841

68

4

8.93

60

0.26

Master's

Full-Time

Married

No Mortgage

No Dependents

Education

No Co-Signer

Predict

Loan Default Prediction Result

Prediction: no default

Loan Default Prediction Result

Prediction: default

Conclusion

- By identifying high-risk loans early, financial institutions can take proactive measures to mitigate losses.
- Some of the key factors influencing loan default are age, income, loan amount,credit score, and employment status.
- Future steps include exploring advanced algorithms and real time data for enhanced model performance.

Reference

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2.ManjeetKumar, Vishesh Goel, Tarun Jain, Sahil Singhal,DR. Lalit Mohan Goel. (2018). Neural Network Approach To Loan Default Prediction, International Research Journal of Engineering and Technology (IRJET) , p-ISSN: 2395-0072

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Thank You !