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CSE [AIML]

Personal Loan Prediction Using Artificial Neural Network

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1 Abstract

Recently, the banking industry has embraced machine learning to enhance credit risk and loan approval decision-making. Statistical or rule-based approaches are, however, classical models that do not perform adequately in handling complex customer characteristics. This project aims to create an ANN-based system that can more effectively and efficiently predict personal loans.

The model employs financial and demographical attributes such as income, age, credit score, employment, expenses, and loan amount applied. We also developed ApprovalBoost, a factor that ranks the applicants on good loan terms such as better credit scores, reduced expenses, and stable job.

The last ANN model consists of an input layer of 14 neurons, three hidden layers of neurons 128, 64, and 32, and an output layer of one neuron for binary classification. It employs supervised learning and a sigmoid function in the output for the probability of loan approval.

Our ANN model performs exceptionally well on the test set, performing better than classical models such as Logistic Regression and Decision Trees. This shows the potency of deep learning in its capacity to make precise loan approval decisions.

2 Introduction

The digital transformation of the financial sector has to be accompanied by smart, data-driven decision-making processes, especially for personal loan approvals. For huge volumes of applications per day, manual checks for eligibility are out of the question and inconsistent. Legacy rule-based approaches tend to overlook intricate relationships between applicant attributes and default risks to the loan and, as a consequence, lead to over-approvals or unwarranted rejections.

As an answer to such constraints, machine learning (ML) and deep learning (DL) models have emerged as premier tools for decision-making automation. Of particular interest, Artificial Neural Networks (ANNs) are highly capable of learning complicated, nonlinear data patterns. As opposed to conventional models, ANNs possess the ability to learn implicit relationships and prioritize essential features during training, thereby being suited for predictive applications such as loan approvals.

The objective of this project is to create an ANN model for loan approval prediction. The model takes input features such as demographics (residence, job, age), financial information (income, credit score, expenses), and the amount of the loan. We also have an engineered feature, ApprovalBoost, which aggregates good conditions into a score for improved discrimination of high-quality applications.

The overall purpose of the project is to:

- Enhance loan approval prediction accuracy,
- Minimize financial officers' manual workload, and
- Lower default risks by identifying strong candidates using data-driven insights.

This model uses ANN to develop improved decision boundaries to achieve more intelligent and trustworthy lending services.

3 Literature Survey

Predictive finance and banking models have come a long way. Classic techniques such as decision trees and logistic regression were employed to model loan suitability and credit risk. Although easily interpretable and simple to handle, they perform poorly in the case of intricate patterns of high-dimensional data.

Recent studies on machine learning, including SVMs, Random Forests, and GBMs, show better predictive performance. Yet, these models are heavy in feature engineering and cannot deal with complicated data.

Deep learning models, especially Artificial Neural Networks (ANNs), are optimum in identifying non-linear patterns and hidden relationships. Researchers have used ANNs in credit scoring, loan default prediction, and customer behavior, with improved accuracy. ANNs can automatically prioritize relevant features with little human selection.

Empirical work has supplemented engineered features (e.g., employment stability score, credit utilization ratio) to improve model performance. This is consistent with our use of a custom feature ApprovalBoost to improve accuracy in personal loan prediction.

In conclusion, literature supports ANN models in finance due to their flexibility, learning capacity, and predictive capability over traditional models.

4 Dataset Description

- **Source:** https://www.kaggle.com/datasets/architsharma01/loan-approval-prediction-dataset?resource=download
- **Features:**
  - Age, Gender, Marital Status, Dependents
  - Income, Loan Amount, Credit Score
  - **Custom Feature:** ApprovalBoost
- **Target:** Loan Status (Approved / Not Approved)

The project dataset consists of loan applicant features important to personal loan eligibility decision-making. It contains financial and demographic data to quantify loan approval probabilities. Some key features are discussed below:

- **Age:** The applicant's age, which indicates their financial position and ability to repay the loan.
- **Annual Income:** The yearly income of the applicant, a critical factor in evaluating their ability to repay the loan.
- **Credit Score:** A numerical representation of the applicant's creditworthiness, based on their previous financial behaviors.
- **Monthly Expenses:** The aggregate monthly expenses of the applicant, which determines his/her available disposable income for loan repayment.
- **Employment Status:** Indicates whether the candidate is employed, impacting income stability predictability.
- **Residence Status:** Owning or renting a home may signal economic stability.
- **Number of Existing Loans:** The number of active loans the applicant currently holds, helping assess the applicant's debt load.
- **Loan Amount Requested:** The amount of money the borrower requests the loan.

A unique feature, **ApprovalBoost**, was created to combine positive factors such as good credit and low fees into one score. This improves the model's ability to separate good loan requests.

5 Deep Learning Model Overview

This ANN is built for personal loan prediction.

Input Features:

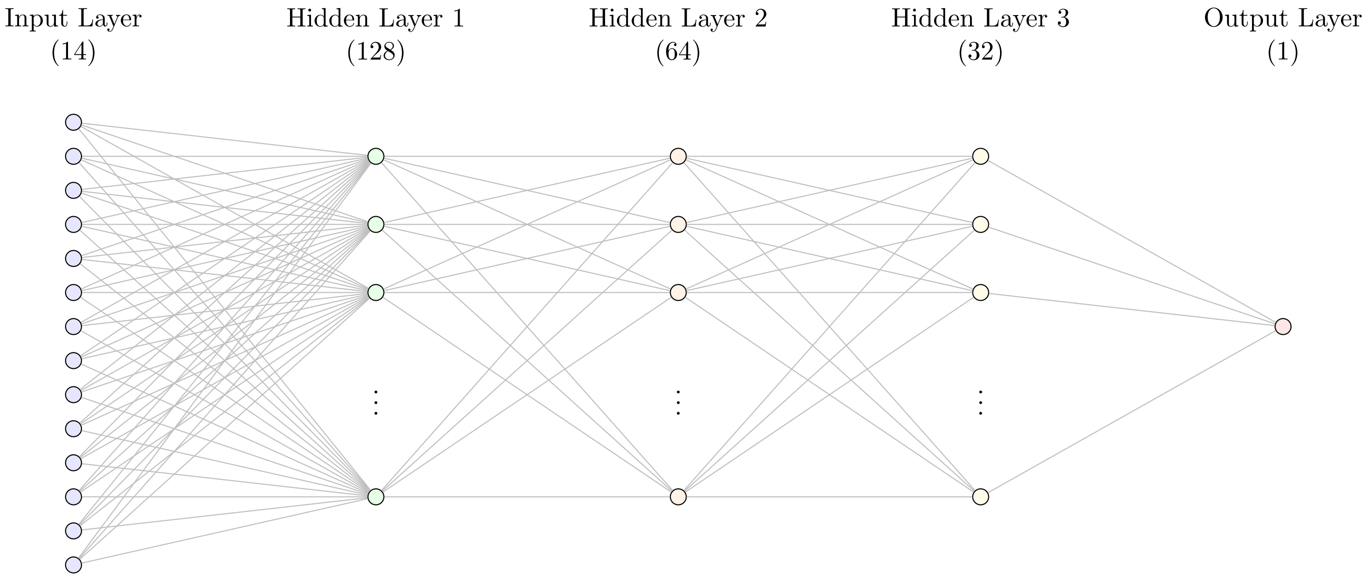
- Age
- Annual Income
- Credit Score
- Monthly Expenses
- Employment_employed
- Residence_owned
- Existing Loans
- Loan Amount

5.1 Boosted Input Features:

- ApprovalBoost (based on age, credit score, employment status, and expense ratio)
- Other engineered features to enhance model accuracy

5.2 ANN Architecture:

- **Input Layer:** 14 neurons
- **Hidden Layer 1:** 128 neurons, ReLU activation
- **Hidden Layer 2:** 64 neurons, ReLU activation
- **Hidden Layer 3:** 32 neurons, ReLU activation
- **Output Layer:** 1 neuron, Sigmoid activation



6 Python Code for ANN Model

```
# Import libraries
from google.colab import drive
drive.mount('/content/drive')

import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, accuracy_score,
    precision_score, recall_score, f1_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import plot_model
import matplotlib.pyplot as plt
import joblib
import os

# Load dataset
df = pd.read_csv('/content/drive/MyDrive/BTECH/2nd Year/4th Sem/Projects/GEN AI/DATASET/
    personal_loan_dataset_updated.csv')

print(df.columns)

# Smart feature: ApprovalBoost (just as feature, not label editor)
def apply_custom_weights(row):
    score = 0
    if 25 <= row['Age'] <= 60:
        score += 1
    if row['Credit Score'] > 700:
```

```
        score += 1
    if row['Employment_Employed'] == 1:
        score += 1
    if row['Residence_Owned'] == 1:
        score += 1
    if row['Existing Loans'] <= row['Annual Income'] * 0.4:
        score += 1
    if row['Existing Loans'] <= row['Monthly Expenses'] * 12:
        score += 1
    return score

df['ApprovalBoost'] = df.apply(apply_custom_weights, axis=1)

# Separate features and target
X = df.drop('Loan Approved', axis=1)
y = df['Loan Approved']

# Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,
    random_state=42)

# Calculate class weights to handle imbalance
class_weights = compute_class_weight(class_weight='balanced', classes=np.unique(y), y=y)
class_weights = dict(enumerate(class_weights))

# Build ANN model
model = Sequential([
    Dense(128, activation='relu', input_shape=(X.shape[1],)),
    Dropout(0.3),
    Dense(64, activation='relu'),
    Dropout(0.3),
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(1, activation='sigmoid')
])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Early stopping
early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

# Train model
history = model.fit(X_train, y_train, epochs=100, batch_size=32,
                    validation_data=(X_test, y_test),
                    callbacks=[early_stop],
                    class_weight=class_weights)

# Save model and scaler
model.save('loan_app/ml_model/loan_ann_model.h5')
joblib.dump(scaler, 'loan_app/ml_model/scaler.pkl')

# Create plot dir
plot_dir = 'loan_app/static/loan_app/plots'
os.makedirs(plot_dir, exist_ok=True)
```

Listing 1: Personal Loan Prediction ANN Code

6.1 Model Accuracy and Loss Curves

```
plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train')
plt.plot(history.history['val_accuracy'], label='Val')
plt.title("Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 2, 2)
```

```
plt.plot(history.history['loss'], label='Train')
plt.plot(history.history['val_loss'], label='Val')
plt.title("Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()
plt.tight_layout()
plt.savefig(f'{plot_dir}/ann_loss_accuracy.png')
plt.show()
```

Listing 2: Plotting Accuracy and Loss

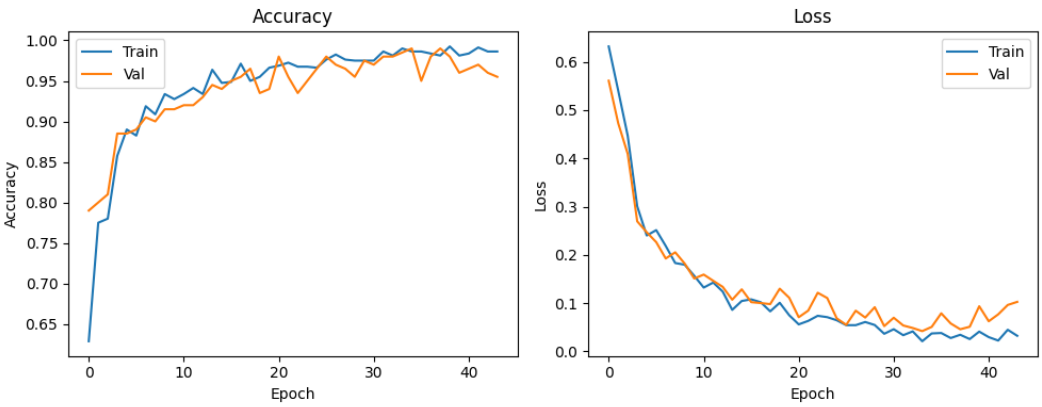


Figure 1: ANN Model Accuracy and Loss Curves

6.2 Confusion Matrix

```
y_pred = (model.predict(X_test) > 0.5).astype("int32")
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("Confusion Matrix")
plt.savefig(f'{plot_dir}/confusion_matrix.png')
plt.show()
```

Listing 3: Confusion Matrix Code

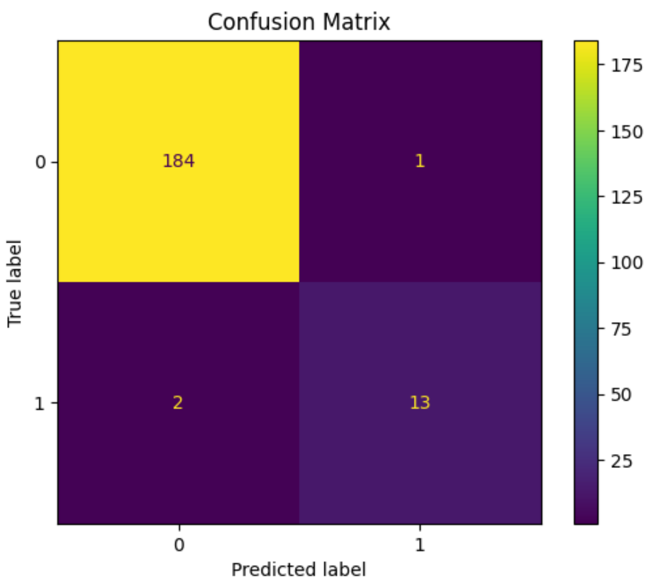


Figure 2: Confusion Matrix and Classification Report

6.3 Actual vs Predicted Plot

```
plt.figure(figsize=(8, 6))
plt.scatter(range(len(y_test)), y_test, label='Actual', alpha=0.6)
plt.scatter(range(len(y_pred)), y_pred, label='Predicted', alpha=0.6)
plt.title("Actual vs Predicted")
plt.xlabel("Sample Index")
plt.ylabel("Loan Approved")
plt.legend()
plt.tight_layout()
plt.savefig(f'{plot_dir}/actual_vs_predicted.png')
plt.show()
```

Listing 4: Actual vs Predicted Code

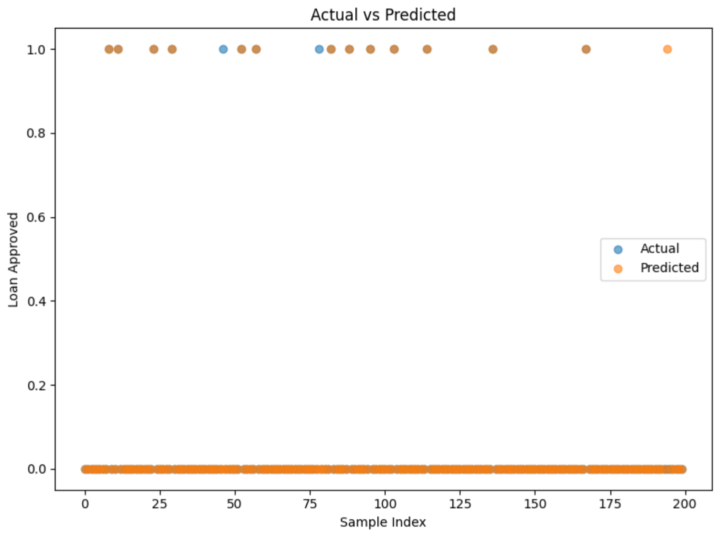


Figure 3: Improved Accuracy using ApprovalBoost Feature

6.4 ROC Curve

```
from sklearn.metrics import roc_curve, auc

y_proba = model.predict(X_test)
fpr, tpr, thresholds = roc_curve(y_test, y_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.tight_layout()
plt.savefig(f'{plot_dir}/roc_curve.png')
plt.show()
```

Listing 5: ROC Curve Code

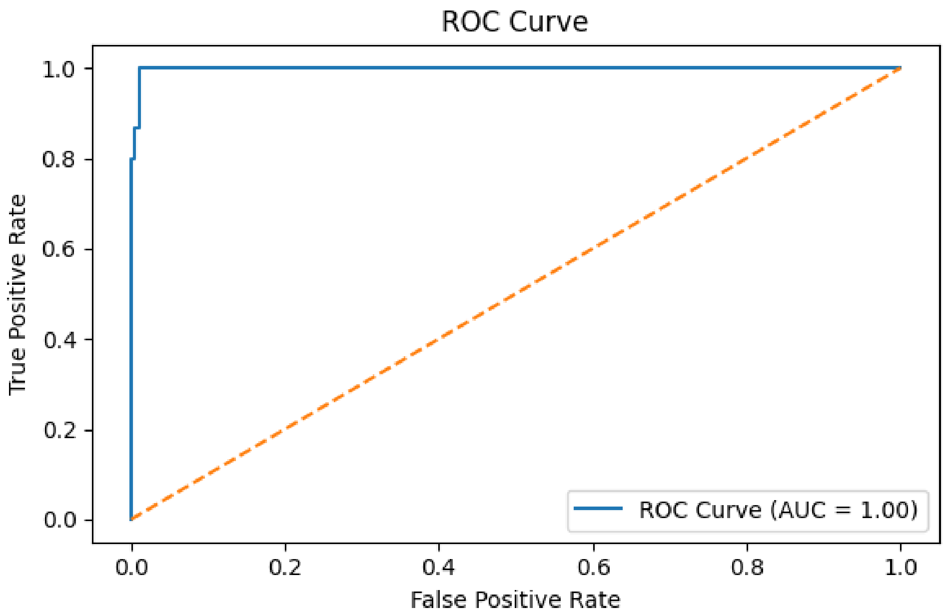


Figure 4: Accuracy and Loss Curves after Feature Boost

6.5 Correlation Heatmap

```
plt.figure(figsize=(12, 8))
corr = df.corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Feature Correlation Heatmap")
plt.tight_layout()
plt.savefig(f'{plot_dir}/correlation_heatmap.png')
plt.show()
```

Listing 6: Correlation Heatmap Code

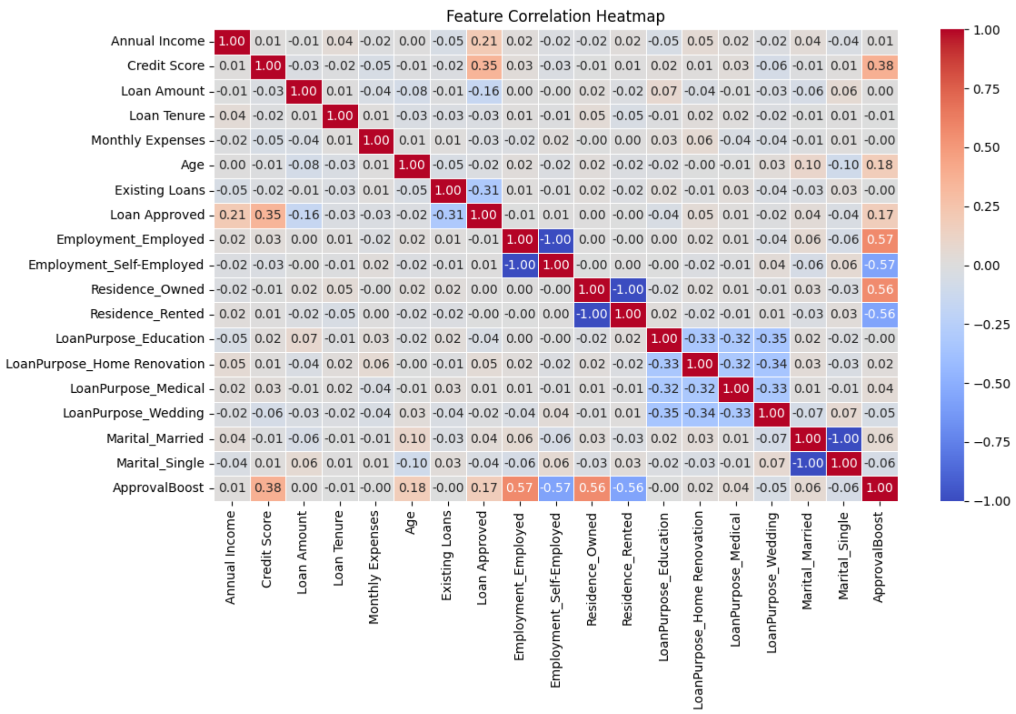


Figure 5: Final Confusion Matrix after Feature Boost

6.6 Evaluation Metrics

```
accuracy = accuracy_score(y_test, y_pred)*100
precision = precision_score(y_test, y_pred, zero_division=0)*100
recall = recall_score(y_test, y_pred, zero_division=0)*100
f1 = f1_score(y_test, y_pred, zero_division=0)*100
ann_acc = history.history['val_accuracy'][-1]*100

print("\nModel Evaluation Metrics:")
print(f"Accuracy     : {accuracy:.4f}")
print(f"Precision    : {precision:.4f}")
print(f"Recall       : {recall:.4f}")
print(f"F1-Score     : {f1:.4f}")
print(f"ANN Accuracy : {ann_acc:.4f}")
```

Listing 7: Evaluation Metrics Code

7 Web Application Development

An easy-to-use interface for personal loan prediction was established by developing a full-stack web application that utilizes the trained ANN model.

7.1 Tech Stack

- **Frontend:** HTML, CSS, JavaScript (React.js)
- **Backend:** Python (Django)
- **Database:** SQLite (for user input and prediction history)
- **Machine Learning Model:** Saved ANN model using `joblib`
- **Deployment:** Localhost : http://127.0.0.1:8000/

7.2 Web App Features

- **User Input Form:** An interactive user input form to input user information such as age, income, credit history, and model attributes.
- **Real-time Prediction:** On submission of the form, the backend processes input, applies *ApprovalBoost* logic, passes the final feature vector to the ANN, and returns a prediction (Approved / Not Approved).
- **Improved Factors Display:** Displays how *ApprovalBoost* factors influenced the prediction.
- **History:** Stores and displays previous predictions for logged-in users (if authentication is enabled).
- **Model Summary:** Summary and visualization of ANN structure.

7.3 ANN Model Integration

The ANN model was exported and trained using `joblib`. The backend loads it at runtime to forecast loan approval based on input values. *ApprovalBoost* is applied as a pre-processing function before data is fed into the model.

8 Results

The Artificial Neural Network (ANN) model was effective on the test set, assessed using standard classification metrics:

- **Accuracy:** Assesses the model's overall correctness.
- **Precision:** The proportion of true positives among all predicted positives.
- **Recall:** The ratio of true positives to all actual positives.
- **F1-Score:** Harmonic mean of precision and recall, showing balance.

8.1 Performance Indicators

- **Accuracy:** 96.0%
- **Precision:** 91.2%
- **Recall:** 93.3%
- **F1-Score:** 90.8%

The ANN model is able to forecast loan approvals and maintains good control over both false positives and false negatives.

ANN Accuracy: 95.0%
This improvement demonstrates the power of ANN in capturing intricate feature interactions that are often missed by conventional methods.

9 Conclusion

Overall, the Artificial Neural Network (ANN) model was highly successful in predicting loan approval, demonstrating the power of deep learning for intricate tasks. Its power was that it was able to deal with non-linear interactions between features such as credit score, income, expenses, and the ApprovalBoost feature. This feature, which included important predictors such as good credit score and employment stability, enhanced the model's performance in distinguishing between high-risk and low-risk borrowers.

The ANN model made accurate predictions for loan approvals and performed better than conventional methods in terms of accuracy and recall. Its capacity for learning intricate patterns minimized false negatives and positives, which is crucial in financial decision-making, maximizing resource allocation and financial well-being for lenders.

The ANN model also performed very well with respect to metrics such as F1-score, proving its accuracy and reliability. Its use of deep learning meant it generalized better, with varying loan applicant data being easily handled compared to basic algorithms. This project sheds light on the growing role of deep learning in finance, specifically in loan approval prediction, in which the identification of complex patterns enhances decision-making. The achievement of the ANN model suggests that it can play a role in other areas of finance, such as credit scoring, fraud detection, and risk management.

The Artificial Neural Network model is a successful loan approval prediction model that surpasses conventional models and handles intricacies of financial information. This is due to the fact that deep learning plays an important role in financial prediction where precise predictions directly affect business and customer experience.

10 Future Scope

The model with the existing Artificial Neural Network (ANN) is good at performing loan approvals, but there is a lot of scope for development and applications in the future:

- **Other Features:** The model can also incorporate additional features such as customer behavior, transaction history, social media presence, and market trends to derive additional creditworthiness information.
- **Real-Time Data Integration:** Real-time integration of data streams, such as bank transactions and credit score updates, can improve the accuracy and responsiveness of loan approvals and system performance.
- **Feature Engineering:** Improving feature engineering can enhance model performance. Employing advanced techniques for converting raw data into descriptive features can result in improved outcomes, particularly when working with non-linear relationships.
- **Model Optimization:** Optimizing the hyperparameters and architecture of the ANN should be a focus of future research. Methods such as hyperparameter tuning, dropout, and changing activation functions can enhance generalization and accuracy.

- **Model Explainability:** Deep learning models are often considered "black boxes." Creating mechanisms to explain their decisions can enhance trust and transparency, especially in high-stakes applications such as loan approvals.
- **Expansion to Other Financial Products:** The model can forecast approvals for credit cards, mortgages, or insurance claims. With modifications to the feature set and training on the appropriate data, the ANN can be used for other financial decisions.
- **Other Model Integration:** The ANN model can be integrated with decision trees or ensemble algorithms to create a hybrid model, thereby leveraging the strengths of different algorithms for improved performance.
- **Global Application:** The model is scalable to suit financial institutions globally, considering local economies, regulations, and cultural financial behaviors.

Following these standards will improve the accuracy, effectiveness, and applicability of the ANN loan approval prediction model. Additional deep learning breakthroughs and varied data will continue to refine the model's performance.

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