Loan Approval Prediction

1. Introduction

Objective: Build a predictive model to classify loan applications as approved (no default) or rejected (default risk), enabling lenders to identify high-risk loans before disbursal.

Motivation: Early detection of potential defaults helps financial institutions reduce losses, optimize credit underwriting, and allocate resources more efficiently.

2. Data Description

- **Source:** loan_data.csv containing attributes of past loan applicants.
- **Target Variable:** loan_status (binary: Approved = 1, Rejected/Default = 0).
- **Features:**
  - **Categorical (5):** person_gender, person_education, person_home_ownership, loan_intent, previous_loan_defaults_on_file
  - **Numerical (~20+):** Income, annual debt, credit scores, loan amount, interest rate, etc.

3. Data Preprocessing

1. **Train/Val/Test Split:**
   - 60% training, 20% validation, 20% test (stratified by loan_status).
2. **Pipeline (ColumnTransformer):**
   - **One-hot encoding** of categorical features (drop='first' to avoid multicollinearity).
   - **Min–Max scaling** of numerical features into [0,1].
3. **Class Weights:** Computed via sklearn.utils.class_weight to counteract imbalance during model training.

4. Model Development

4.1 Baseline Neural Network

- **Architecture (Keras Sequential):**
  1. Dense(64, relu) → Dropout(0.3)
  2. Dense(32, relu) → Dropout(0.3)
  3. Dense(1, sigmoid) for binary classification

- **Compilation:**
    - Optimizer: Adam
    - Loss: Binary Crossentropy
    - Metric: Accuracy
- **Training:**
    - Epochs: up to 50
    - Batch size: 32
    - EarlyStopping (patience=5, restore best weights)
    - ModelCheckpoint to save best model
    - Class weights applied
- **Results:**

  Confusion Matrix and Classification Report:
  Accuracy = 88.7%

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✅ Test Accuracy: 0.887

🔍 Confusion Matrix:
 [[6240  760]
 [ 257 1743]]

📋 Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.89      0.92      7000
           1       0.70      0.87      0.77      2000

    accuracy                           0.89      9000
   macro avg       0.83      0.88      0.85      9000
weighted avg       0.90      0.89      0.89      9000
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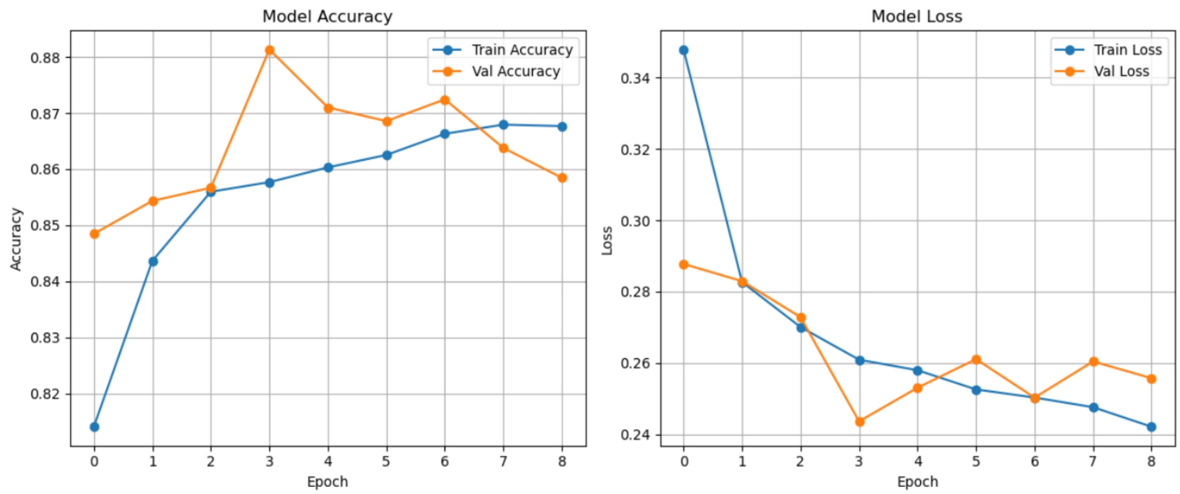
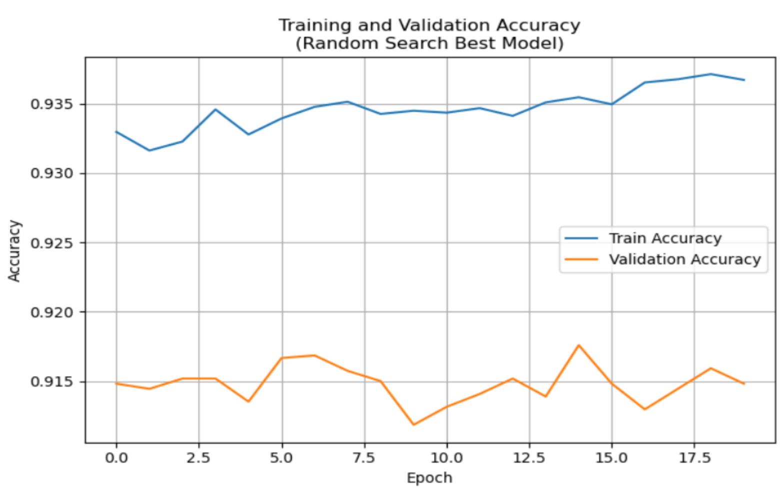
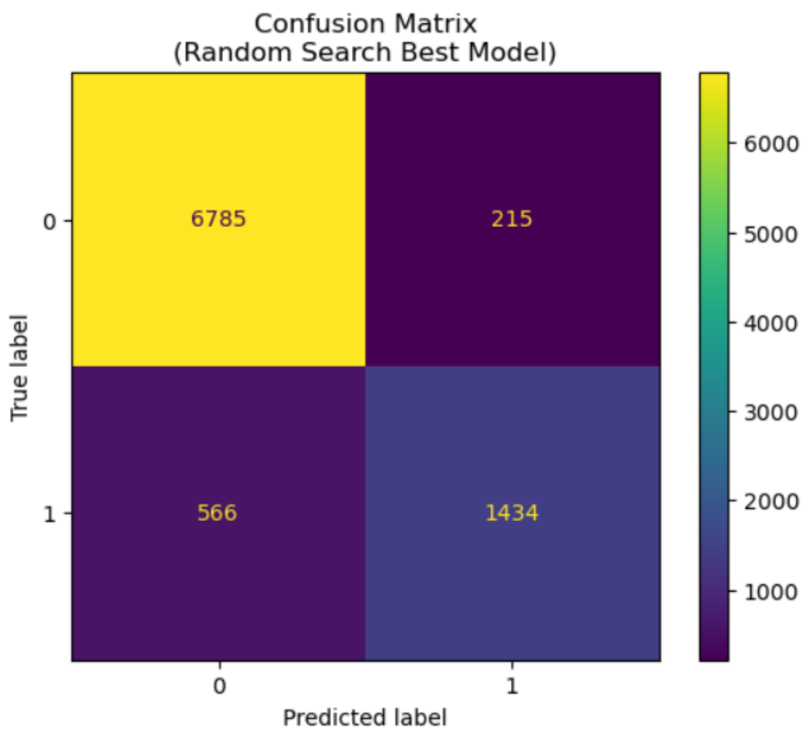
Model Accuracy and Loss graphs for training and validation for base model:



4.2 Hyperparameter Tuning (Keras Tuner)

- **Methods compared:**
  - Random Search
  - Bayesian Optimization
  - Hyperband
- **Hyperparameters tuned:** number of units in hidden layers (32–256), dropout rates (0.0–0.5), learning rate, etc.
- **Evaluation:** Best model from each tuner evaluated on the held-out test set; accuracies compared in a summary table.
- **Results:** Best model from each tuner evaluated on the held-out test set; accuracies compared in a summary table.





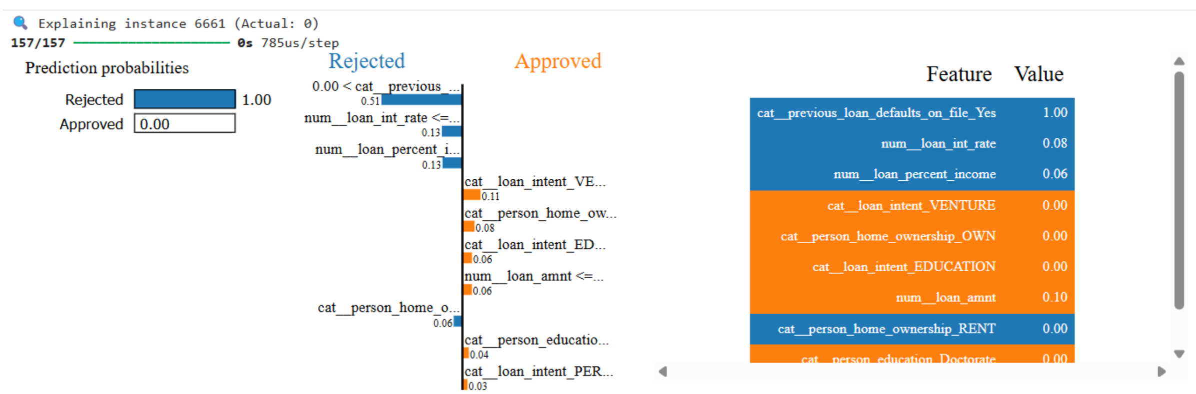
Based on the held-out test accuracies:

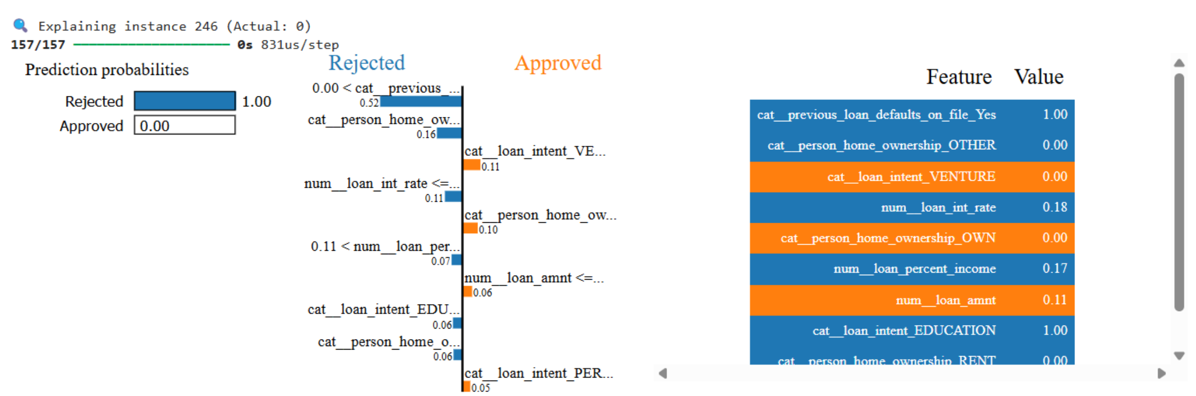
Tuning Method	Test Accuracy
Random Search	**0.92078**
Hyperband	0.91889
Bayesian Optimization	0.91767

– **Random Search** gives the highest test accuracy (≈ 92.08%), narrowly beating Hyperband (≈ 91.89%).
– The validation curves are all very close, but Random Search also reached the top validation accuracy (~ 0.9211).

5. Conclusion

- **Baseline Model Performance:**
  - Test accuracy: ≈ *88.7%*
  - Confusion matrix and classification report showed precision/recall trade-offs.
- **Hyperparameter Tuning:**
  - Random Search: ≈*92.1%*
  - Bayesian Opt.: ≈ *91.7 %*
  - Hyperband: ≈ *91.9 %*
  - Best overall: **Random Search** with 92.1% test accuracy.
- **Model Interpretability:**
  - LIME explanations generated for sample test instances, highlighting top features driving approval/rejection decisions.





Main observations from LIME visual:

- **History of Prior Defaults:** The feature previous_loan_defaults_on_file = Yes is the strongest driver toward rejection, indicating the model heavily penalizes applicants with past defaults.
- **Financial Risk Indicators:** Higher values of loan_int_rate and loan_percent_income consistently push predictions toward rejection, showing the model views expensive or high-leverage loans as higher risk.
- **Loan Intent Effects:** Certain intents (e.g., "Venture" or "Education") can slightly counterbalance rejection or approval, but their impact is relatively modest compared to credit-worthiness indicators.
- **Home Ownership Status:** Applicants who own (or rent) their home see small shifts in predicted risk—the model incorporates stability signals from housing status, though less strongly than financial metrics.

These explanations confirm that both numeric ratios and key categorical signals drive the model's decisions, and they can guide feature-engineering or business rules for future iterations.

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6. Challenges Faced & Solutions

- **Class Imbalance**
  - ***Challenge**:* Far fewer defaults than approvals made the model biased toward the majority class.
  - ***Solution:*** Computed and applied class weights during training and used stratified splits to ensure balanced representation in train/validation/test sets.
- **Overfitting on Training Data**
  - ***Challenge:*** The network rapidly reached high training accuracy but then degraded on validation.
  - ***Solution:*** Added Dropout layers, employed EarlyStopping with patience, and restored the best weights to curb overfitting.
- **Long Hyperparameter Search Times**
  - ***Challenge:*** Extensive tuning with multiple methods (RandomSearch, Bayesian, Hyperband) proved time-consuming.
  - ***Solution:*** Limited trials and executions per trial, leveraged Hyperband's adaptive scheduling, and parallelized searches where possible.
- **High-Cardinality Categorical Features**

    - ***Challenge:*** One-hot encoding dozens of categories inflated input dimensionality.
    - ***Solution:*** Applied drop_first=True to reduce redundancy and in future could explore embedding layers for large vocabularies.
- **Model Interpretability**
    - ***Challenge:*** Deep models are complicated and might be difficult to understand for stakeholders.
    - ***Solution:*** Integrated LIME/SHAP explanations to surface the top drivers of each individual prediction, validating that key credit-worthiness signals (e.g., prior defaults, interest rate) dominate.