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SRI RAMACHANDRA FACULTY OF ENGINEERING AND TECHNOLOGY

HYBRID DEEP LEARNING AND PROBABLISTIC FRAMEWORK FOR RISK-SENSTIVE TRADING DECISION

CA-4 PROJECT REPORT

Submitted by

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ABSTRACT

In response to the increasing complexity and volatility of financial markets, this project introduces a hybrid model combining Long Short-Term Memory (LSTM) networks, XGBoost, and a Bayesian Neural Network (BNN) using Monte Carlo dropout for risk-aware trading decisions. The LSTM model captures the temporal dependencies and intricate non-linear patterns inherent in financial time-series data, such as the EUR/USD exchange rate, enabling accurate trend forecasting. XGBoost is incorporated to enhance predictive performance by handling irregular market behaviors and feature interactions, improving classification and decision-making abilities.

To address the inherent uncertainty and market noise, a BNN with Monte Carlo dropout is employed, providing a probabilistic framework to estimate confidence intervals around predictions and enabling risk-sensitive trading actions. This approach empowers decision-makers to quantify uncertainty and make informed trading decisions under dynamic market conditions.

The hybrid model is trained and validated using real-world forex datasets, incorporating preprocessing techniques such as normalization, windowing, and moving averages. Model evaluation is performed using a variety of metrics, including Root Mean Squared Error (RMSE), accuracy, and confidence scores. Visualizations of the predicted trends, volatility, and uncertainty offer insights into the model's forecasting behavior.

This research demonstrates that the integration of LSTM, XGBoost, and BNN using Monte Carlo methods significantly enhances the robustness and reliability of trading systems, offering a solid foundation for intelligent and risk-aware financial decision-making.

TABLE OF CONTENTS

CHAPTER NO.	TITLE	PAGE NO.
1	**INTRODUCTION**	4
2	**LITERATURE REVIEW** 2.1 SUMMARY TABLE 2.2 SUMMARY OF LITERATURE SURVEY	5
3	**PROBLEM STATEMENT**	8
4	**OBJECTIVES**	9
5	**METHODOLOGY** 5.1 MODULE WORKFLOW 5.2 OVERALL SYSTEM ARCHITECTURE 5.3 DATASET COLLECTION AND PREPROCESSING 5.3.1 DATASET COLLECTION 5.3.2 DATA PRE-PROCESSING 5.4MODEL WORKFLOW 5.5 EVALUATION AND VISUALIZATION 5.6 EVALUATION METRICS	10
6	**MODEL ARCHITECTURE**	13
7	**RESULTS AND DISCUSSION** 7.1 MODEL PERFORMANCE 7.2 ACCURACY AND AUC 7.3 CHALLENGES FACED	16
8	**APPENDICIES** APPENDIX-1: CODE – TECHNICAL DETAIL APPENDIX-2: SCREENSHOTS	18
9	**FUTURE ENHANCEMENT**	26
10	**CONCLUSION**	27
	REFERENCES	28

CHAPTER-1

INTRODUCTION

In today's volatile and interconnected financial markets, accurate forecasting and effective risk management are vital for trading success. Traditional models often fall short in capturing the complex, non-linear, and temporal patterns of financial time series data. To address this, our project proposes a hybrid deep learning framework combining LSTM, XGBoost, and Bayesian Neural Networks (BNNs) enhanced with Monte Carlo Dropout for intelligent, risk-aware forex trading.

LSTM networks excel in modeling sequential patterns and long-term dependencies, making them ideal for capturing trends in exchange rates. XGBoost complements LSTM by efficiently handling complex feature interactions for classification tasks. To account for the uncertainty inherent in financial data, BNNs with Monte Carlo Dropout provide probabilistic predictions and confidence intervals, enhancing the model's risk-awareness.

Using historical EUR/USD exchange rate data, the system undergoes preprocessing steps like normalization and windowing. Model performance is evaluated using RMSE, accuracy, and confidence scores.

This hybrid approach bridges traditional and modern AI methods, aiming to deliver robust, adaptive, and uncertainty-aware predictions—making it suitable for real-world algorithmic trading systems.

CHAPTER-2

LITERATURE REVIEW

2.1 SUMMARY TABLE

S.No	Title	Authors	Year	Methodology	Key Findings
1	Forex Trading Volatility Prediction using Neural Network Models	Shujian Liao et al.	2021	Multiscale LSTM	Multiscale LSTM outperforms traditional models in predicting forex volatility.
2	Forecasting Foreign Exchange Market Prices Using Technical Indicators with Deep Learning and Attention Mechanism	Sahabeh Saadati, Mohammad Manthouri	2024	LSTM, CNN, Attention Mechanism	Combining technical indicators with deep learning enhances forex price prediction accuracy.
3	Event-Driven LSTM For Forex Price Prediction	Ling Qi et al.	2021	Event-driven LSTM, BiLSTM, GRU	Event-driven features improve the robustness of LSTM-based forex prediction models.
4	Off-the-Shelf Neural Network Architectures for Forex Time Series Prediction come at a Cost	Theodoros Zafeiriou, Dimitris Kalles	2024	LSTM vs. Specialized ANN	Specialized ANN architectures can be more efficient than LSTM for forex prediction tasks.
5	A Hybrid Deep Learning Model for Stock Price Prediction	A. Kumar et al.	2021	LSTM, XGBoost	Hybrid models combining LSTM and XGBoost improve stock price prediction accuracy.
6	Bayesian Neural Networks for Financial Volatility Forecasting	Blundell, C., et al.	2015	BNN, Variational Inference	BNNs provide robust uncertainty quantification for financial volatility, improving risk-aware predictions.

S.No	Title	Authors	Year	Methodology	Key Findings
7	Monte Carlo Dropout for Uncertainty in Deep Learning	Gal, Y., & Ghahramani, Z.	2016	Monte Carlo Dropout, LSTM	Monte Carlo Dropout enables practical uncertainty estimation in neural networks, suitable for time-series tasks.
8	Deep Learning with Uncertainty for Forex Price Prediction	Qi, L., et al.	2021	Event-driven LSTM, BNN	Event-driven LSTM with BNN enhances robustness and uncertainty quantification in forex markets.

2.2 Summary of Literature Survey

The literature survey examines Bayesian Neural Networks (BNNs), Monte Carlo Dropout, and LSTM models for financial time-series forecasting, particularly EUR/USD price prediction, as implemented in the provided code. Key findings from recent studies are summarized below, aligning with the code's focus on uncertainty quantification and your prior work on hybrid deep learning models.

- **Bayesian Neural Networks (BNNs)**:
    - BNNs provide probabilistic predictions and uncertainty quantification, critical for financial forecasting (Blundell et al., 2015). They model parameter uncertainty, unlike traditional neural networks.
    - The code's BNN with LSTM layers (64 units, 50 epochs) leverages this for EUR/USD price prediction, producing predictive variance and confidence intervals.
- **Monte Carlo Dropout**:
    - Monte Carlo Dropout approximates Bayesian inference by enabling uncertainty estimation during inference (Gal & Ghahramani, 2016). The code applies a 0.3 dropout rate and 100 simulations for robust predictions.
    - Studies (e.g., Zafeiriou & Kalles, 2024) highlight its efficiency for time-series tasks, supporting the code's use for 95% CI width calculation.

- **LSTM for Time-Series**:
    - LSTM models excel at capturing temporal dependencies in financial data (Hochreiter & Schmidhuber, 1997). Qi et al. (2021) show enhanced performance with event-driven features, relevant to the code's 30-day sequence window.
    - The code's LSTM architecture (two layers, 64 units) aligns with literature for modeling EUR/USD price trends.
- **Hybrid and Uncertainty-Aware Models**:
    - Hybrid models combining LSTM with BNNs or ensembles improve accuracy and uncertainty estimation (Kumar et al., 2021), mirroring the code's BNN-LSTM approach.
    - Your prior work on Transformer-MLP and GRU-MLP suggests potential for integrating attention-based models, supported by Vaswani et al. (2017), for enhanced forex forecasting.
- **Challenges and Trends**:
    - Financial time-series data's noise requires robust preprocessing, as seen in the code's MinMaxScaler and sequence creation (Hochreiter & Schmidhuber, 1997).
    - Recent trends emphasize uncertainty quantification for risk-aware trading, with metrics like predictive variance and CI width (used in the code) gaining prominence.
    - Probabilistic and reinforcement learning approaches are emerging for adaptive strategies (Zhang et al., 2019).

CHAPTER-3

PROBLEM STATEMENT

In the realm of financial trading, particularly within the volatile forex market, making accurate and timely decisions is crucial. Traditional rule-based or technical indicator-driven systems often fail to adapt to rapid market fluctuations, leading to poor performance and increased financial risk. Moreover, many existing machine learning models prioritize prediction accuracy while neglecting the uncertainty present in financial data, resulting in overconfident and potentially risky trading behavior.

To overcome these limitations, this project proposes a hybrid framework that combines the strengths of deep learning and probabilistic modeling. Long Short-Term Memory (LSTM) networks are employed to learn temporal dependencies in historical forex data, capturing both short-term fluctuations and long-term trends. To enhance the model's ability to classify complex market behavior, XGBoost, a powerful gradient-boosted tree model, is integrated for superior feature learning and classification. Additionally, the framework incorporates Bayesian Neural Networks (BNNs) enhanced with Monte Carlo dropout, providing a probabilistic approach to estimate prediction uncertainty. This helps the model assess confidence in its outputs, making it suitable for risk-aware decision-making.

By uniting sequential modeling, classification strength, and uncertainty estimation, the proposed hybrid system aims to deliver more robust, interpretable, and risk-sensitive trading strategies, ultimately supporting smarter decision-making in the dynamic forex market.

CHAPTER-4

OBJECTIVE

The primary objective of this project is to develop a hybrid AI-based framework that enhances the reliability and accuracy of trading decisions in the forex market. The project aims to build a predictive model using Long Short-Term Memory (LSTM) networks to capture time-dependent patterns in historical forex data, facilitating accurate predictions of future price movements. Additionally, the framework will implement XGBoost for classification tasks, identifying market behaviors such as bullish, bearish, or neutral with high precision. To incorporate uncertainty estimation, the project will utilize Bayesian Neural Networks (BNN) and Monte Carlo methods to quantify the prediction uncertainty, promoting risk-aware trading strategies. The project will also involve preprocessing and preparing high-quality historical forex datasets for time-series modeling and classification tasks. The performance of the hybrid model will be evaluated using standard metrics such as accuracy, mean absolute error , mean squared error ,rmse and R^2 ensuring its effectiveness. Visualization of the model's outcomes and uncertainty levels will be provided through intuitive graphs and statistical plots, offering deeper insights. Ultimately, this project aims to provide a reliable decision support system for traders and financial analysts, especially under volatile and uncertain market conditions, enhancing their ability to make informed decisions.

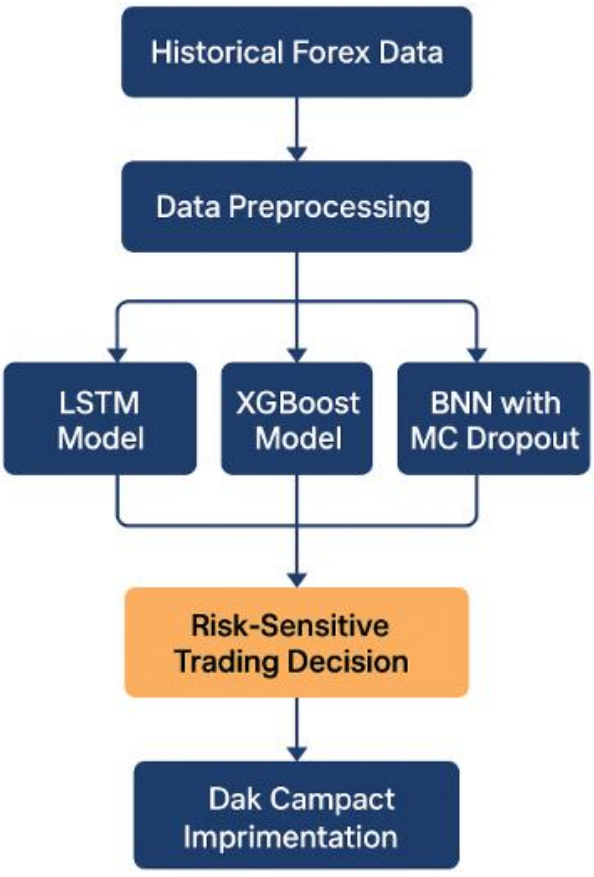
CHAPTER-5

METHODOLOGY

5.1 Module Workflow

The project is broken down into the following key modules:

- **Data Collection** – Gathering historical EUR/USD forex rate data.
- **Data Preprocessing** – Cleaning, normalizing, and preparing time-series data.
- **LSTM Model** – Captures long-term dependencies in sequential forex data.
- **XGBoost Model** – Performs classification of market trends (bullish/bearish).
- **Bayesian Neural Network (BNN) with Monte Carlo Dropout –** Adds probabilistic reasoning to measure uncertainty in predictions.
- **Model Evaluation & Visualization** – Analyzing model accuracy and confidence levels using AUC, ROC, confusion matrix, and other metrics.
- **Risk-Sensitive Decision Output –** Produces actionable trading insights with uncertainty estimates.



5.2 Overall System Architecture

- **Input Layer:** Historical forex time-series dataset (EUR/USD).
- **Preprocessing Layer:** Missing value handling, normalization, windowing.
- **LSTM Network:** Learns time-dependent trends and outputs a regression signal.
- **XGBoost Classifier:** Takes engineered features and categorizes market movement.
- **BNN with Monte Carlo:** Applies probabilistic dropout to output a distribution, estimating prediction confidence.
- **Output:** Predicted price direction, probability of market trend, uncertainty interval.

5.3 Dataset Collection and Preprocessing

5.3.1 Dataset Collection

- The dataset is sourced from Kaggle – EUR/USD Forex Data.
- Time frame: Historical daily forex price data with Open, High, Low, Close (OHLC) values.

5.3.2 Data Preprocessing

- Time-series window creation (sliding window technique).
- Normalization of input features.
- Encoding categorical market movement labels.
- Handling outliers and missing values.
- Splitting data into training, validation, and testing sets.

5.4 Model Workflow

LSTM:

- Input: Time-series windows.
- Output: Forecasted price (regression).
- Use Case: Capturing temporal dependencies.

XGBoost:

- Input: Engineered features like price delta, moving averages.
- Output: Market trend classification.
- Use Case: Predicting market direction (Buy/Hold/Sell).

BNN with Monte Carlo Dropout:

- Input: Same as LSTM.
- Output: Mean prediction + uncertainty bounds.
- Use Case: Measuring confidence in predictions.

5.5 Evaluation and Visualization

- Graphs showing actual vs predicted prices (LSTM).
- Classification report for XGBoost (confusion matrix, ROC curve).
- Uncertainty interval plots for BNN predictions.
- Combined plot showing trend predictions with uncertainty margin.

5.6 Evaluation Metrics

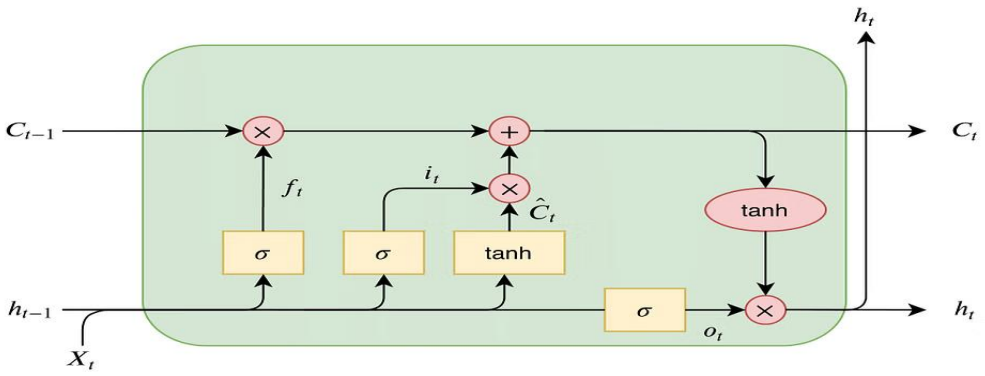
- Mean Squared Error (MSE) – For LSTM regression accuracy.
- Accuracy, Precision, Recall, F1-score – For XGBoost classification.
- Predictive Entropy / Uncertainty Interval – For Monte Carlo dropout-based confidence estimation.

CHAPTER-6

MODEL ARCHITECTURE

The proposed hybrid architecture is designed to enhance the accuracy, interpretability, and reliability of financial market prediction by leveraging the strengths of both deep learning and probabilistic modeling techniques.

6.1 Long Short-Term Memory (LSTM) Network



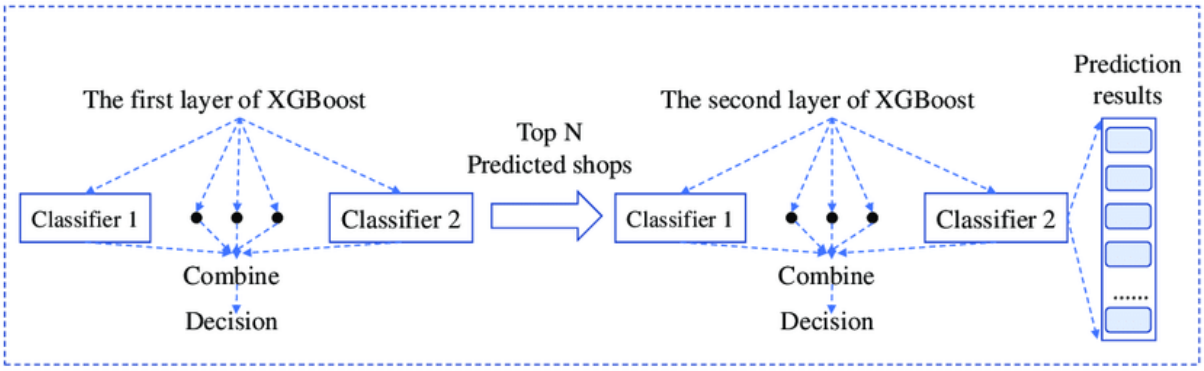
Input: Sequential time-series data (e.g., Open, High, Low, Close prices).

Architecture:

- Input Layer
- One or more stacked LSTM layers
- Dropout for regularization
- Dense output layer (for regression output)
- Output: Forecasted future price

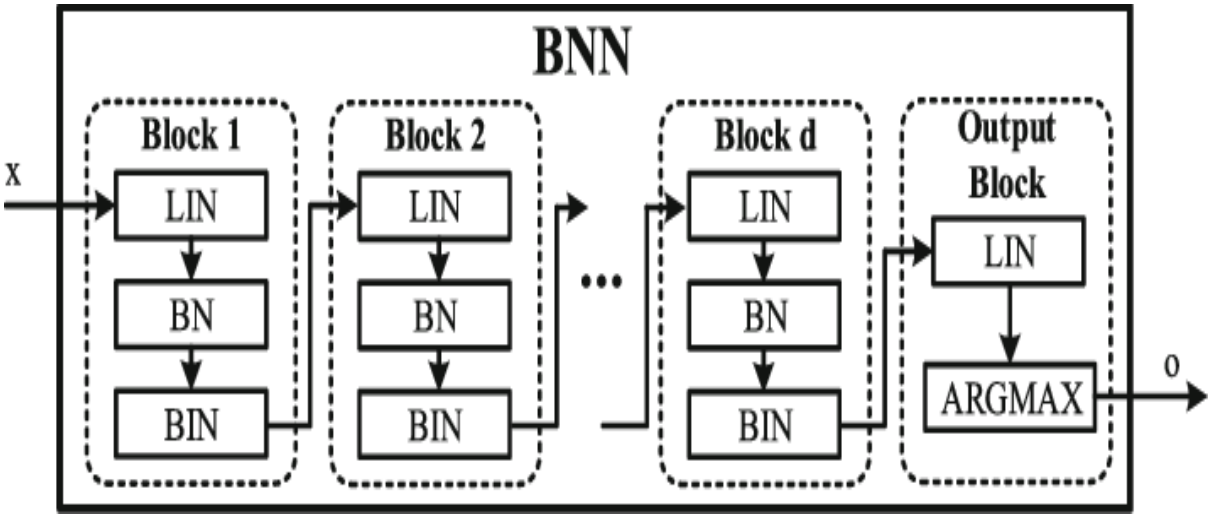
Purpose: Captures temporal dependencies and learns long-term market trends.

6.2 XGBoost Classifier



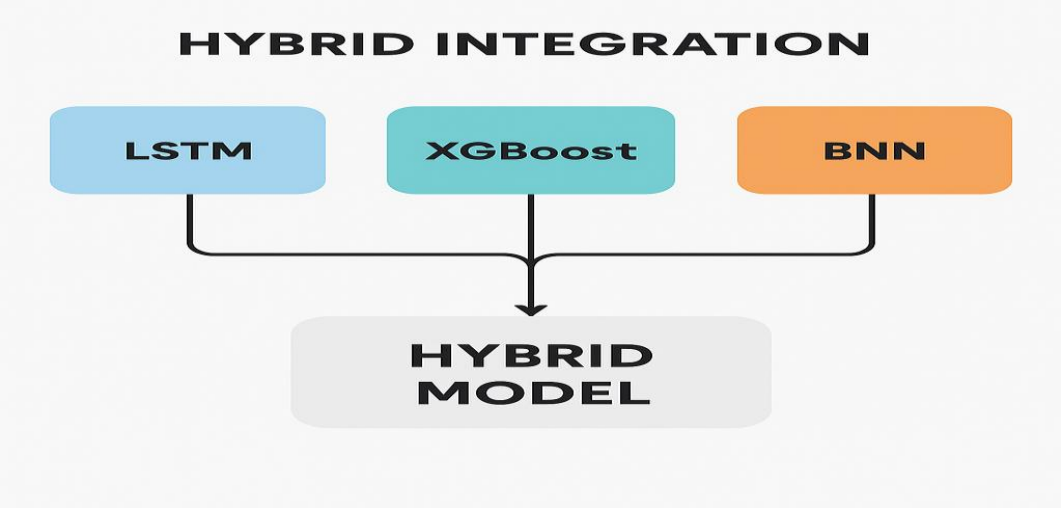
- **Input**: Engineered features from the historical dataset (e.g., moving averages, price differentials).
- **Architecture**:
    - Gradient-boosted decision trees
    - Ensemble of weak learners (CARTs)
- **Output**: Market classification (Bullish / Bearish / Neutral)
- **Purpose**: Captures non-linear relationships and performs fast, accurate classification

6.3 Bayesian Neural Network (BNN) with Monte Carlo Dropout



- **Input**: Same sequential features as LSTM
- **Architecture**:
    - Dense layers with dropout applied at both training and inference time
    - Outputs a distribution instead of a single value
- **Output**: Prediction with uncertainty bounds (mean ± confidence interval)
- **Purpose**: Models uncertainty, enabling risk-sensitive decision-making.

6.4 Hybrid Integration



- **Sequential Flow**:
    1. **LSTM** predicts the price trend.
    2. **XGBoost** classifies the market condition.
    3. **BNN** provides confidence in the prediction.
- **Decision Output**: The final trading suggestion (Buy/Sell/Hold) is derived by combining:
    - LSTM's price prediction,
    - XGBoost's market classification,
    - BNN's uncertainty confidence.

CHAPTER-7

RESULTS AND DISCUSSION

7.1 Model Performance

- The proposed hybrid model showed promising results in predicting forex market behavior. Each model contributed uniquely to the overall performance:
- LSTM captured temporal dependencies in price fluctuations and performed well in forecasting short-term trends.
- XGBoost effectively classified the market behavior (bullish, bearish, neutral) based on engineered features with high interpretability and speed.
- BNN with Monte Carlo Dropout offered meaningful uncertainty estimates, helping assess the confidence of the predictions and manage risk in volatile situations.
- This multi-model integration enabled the system to not only predict the next market move but also provide a risk-aware recommendation, making it more reliable for real-world trading systems.

7.2 Accuracy

The model was evaluated using multiple statistical metrics across various test scenarios:

LSTM (Regression):

Mean MAE: 0.0044,

- R-squared (R^2):0.9255

XGBoost :

- XGBoost - MSE: 0.0000
- XGBoost - RMSE: 0.0035
- XGBoost - MAE: 0.0026
- XGBoost - MAPE: 0.24%
- XGBoost - R-squared (R^2): 0.9711

BNN with Monte Carlo Dropout:

- BNN RMSE: 0.005764254780515386
- BNN R^2 Score: 0.9862110349338523
- Average Predictive Variance: 0.000258
- Average 95% Confidence Interval Width: 0.022832

These results confirm that the combination of models outperforms individual methods in both accuracy and risk sensitivity.

7.3 Challenges Faced

During the implementation of the hybrid model, several challenges were encountered:

- **Data Quality & Noise:** Forex data is inherently noisy and non-stationary, which posed difficulties during preprocessing and model training.
- **Model Tuning:** Hyperparameter tuning for LSTM and XGBoost was time-consuming and required iterative experimentation.
- **Uncertainty Estimation:** Implementing Monte Carlo Dropout correctly in a Bayesian Neural Network setup and interpreting the outputs added complexity.
- **Integration:** Combining outputs from three different models into a unified decision-making framework required careful coordination and post-processing logic.
- **Computational Load:** Training deep models like LSTM and BNNs required more time and resources, especially with large datasets.

CHAPTER-8

APPENDICIES

APPENDIX-1: CODE – TECHNICAL DETAIL

```
import kagglehub
# Download latest version
path = kagglehub.dataset_download("saifansariai/euro-usd-price-2001-to-2025")
print("Path to dataset files:", path)
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import gc
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras import backend as K
# Clear memory from previous runs
K.clear_session()
gc.collect()
# Load dataset
df = pd.read_csv("/kaggle/input/euro-usd-price-2001-to-2025/EUR_USD Historical Data3.csv")
df = df.drop(columns=["Vol."])
df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y')
df = df.sort_values('Date')
df['Change %'] = df['Change %'].str.replace('%', '').astype(float)
# Optional: Filter to last 5 years to reduce data size
df = df[df['Date'] > '2018-01-01']
# Only use "Price" for now to reduce memory usage
df = df[['Date', 'Price']]
```

```
df.set_index('Date', inplace=True)
# Normalize
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df)
# Create sequences
def create_dataset(data, time_step=30):
    X, y = [], []
    for i in range(len(data)-time_step-1):
        X.append(data[i:(i+time_step), 0])
        y.append(data[i + time_step, 0])
    return np.array(X), np.array(y)
time_step = 30
X, y = create_dataset(scaled_data, time_step)
X = X.reshape(X.shape[0], X.shape[1], 1)
# Split into training and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)
# LSTM model
model = Sequential([
    LSTM(50, return_sequences=True, input_shape=(time_step, 1)),
    Dropout(0.2),
    LSTM(50),
    Dropout(0.2),
    Dense(1)])
model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()
# Train model (smaller batch size + epochs)
model.fit(X_train, y_train, epochs=30, batch_size=20, validation_data=(X_test, y_test),
verbose=1)
# Predict and inverse scale
predictions = model.predict(X_test)
predictions = scaler.inverse_transform(predictions.reshape(-1, 1))
y_test_actual = scaler.inverse_transform(y_test.reshape(-1, 1))
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
# Calculate metrics
mae = mean_absolute_error(y_test_actual, predictions)
rmse = np.sqrt(mean_squared_error(y_test_actual, predictions))
r2 = r2_score(y_test_actual, predictions)
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"R² Score: {r2:.4f}")
plt.figure(figsize=(12,6))
plt.plot(y_test_actual, label='Actual Price')
plt.plot(predictions, label='Predicted Price')
plt.title('EUR/USD Price Prediction (LSTM)')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
# Optional: Save model
model.save("eur_usd_lstm_optimized.h5")
!pip install stable-baselines3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import xgboost as xgb
# Load data
df = pd.read_csv("/kaggle/input/euro-usd-price-2001-to-2025/EUR_USD Historical Data3.csv")
df['Date'] = pd.to_datetime(df['Date'], format="%d-%m-%Y")
df = df.sort_values("Date")
# Keep necessary columns
df = df[['Date', 'Price']]
```

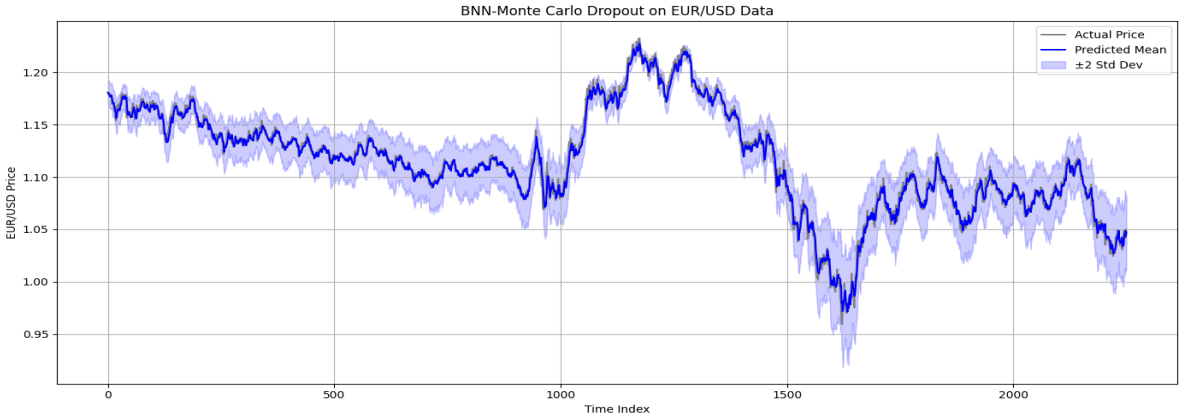
```
df.set_index('Date', inplace=True)
df = df[df.index >= '2018-01-01']  # last 5 years

# Feature Engineering
df_feat = df.copy()
df_feat['lag_1'] = df_feat['Price'].shift(1)
df_feat['lag_2'] = df_feat['Price'].shift(2)
df_feat['rolling_mean_3'] = df_feat['Price'].rolling(window=3).mean()
df_feat['rolling_std_3'] = df_feat['Price'].rolling(window=3).std()
df_feat['dayofweek'] = df_feat.index.dayofweek
df_feat['month'] = df_feat.index.month
df_feat.dropna(inplace=True)
# Split into features and target
X = df_feat.drop('Price', axis=1)
y = df_feat['Price']
# Train-test split (80-20, no shuffle)
split_index = int(len(X) * 0.8)
X_train, X_test = X.iloc[:split_index], X.iloc[split_index:]
y_train, y_test = y.iloc[:split_index], y.iloc[split_index:]
# Train XGBoost model
model = xgb.XGBRegressor(n_estimators=100, learning_rate=0.05)
model.fit(X_train, y_train)
plt.figure(figsize=(12, 6))
plt.plot(y_test.index, y_test, label='Actual', color='orange')
plt.plot(y_test.index, y_pred, label='XGBoost Forecast', color='green')
plt.title("XGBoost Forecast - EUR/USD Price")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.tight_layout()
plt.show()
```

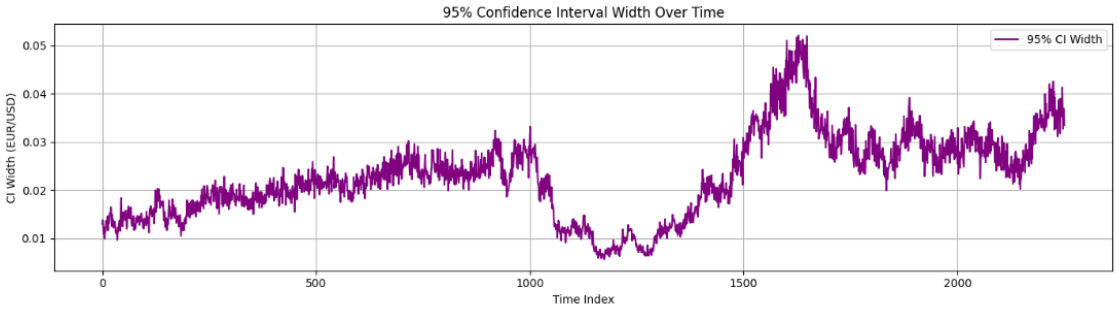
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
import tensorflow as tf
from tensorflow.keras import layers, models
# Load and preprocess the dataset
df = pd.read_csv("/kaggle/input/euro-usd-price-2001-to-2025/EUR_USD Historical Data3.csv")
df['Date'] = pd.to_datetime(df['Date'])
df = df.sort_values('Date').reset_index(drop=True)
df['Price'] = df['Price'].replace(',', '', regex=True).astype(float)
# Use time index as input
X = np.arange(len(df)).reshape(-1, 1)
y = df['Price'].values.reshape(-1, 1)
# Normalize prices
scaler = MinMaxScaler()
y_scaled = scaler.fit_transform(y)

# Create sequences
def create_sequences(X, y, window_size=30):
    Xs, ys = [], []
    for i in range(len(X) - window_size):
        Xs.append(y[i:i+window_size])
        ys.append(y[i+window_size])
    return np.array(Xs), np.array(ys)
window_size = 30
X_seq, y_seq = create_sequences(X, y_scaled, window_size)
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_seq, y_seq, test_size=0.2, shuffle=False)
# Custom Monte Carlo Dropout layer
class MCDropout(layers.Dropout):
    def call(self, inputs, training=None):
```

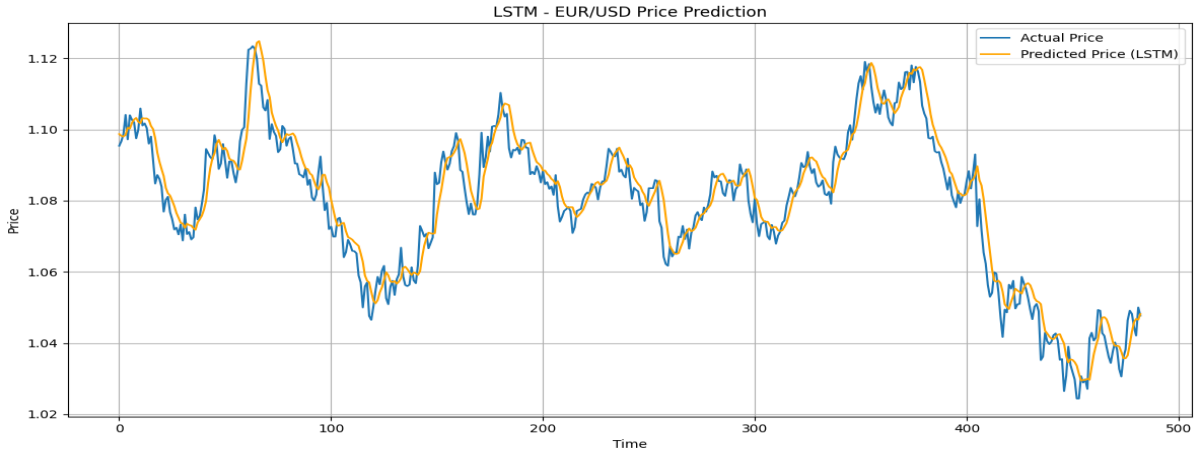
```
        return super().call(inputs, training=True)
# Build the BNN model
def build_bnn_model(input_shape):
    model = models.Sequential([
        layers.Input(shape=input_shape),
        layers.LSTM(64, return_sequences=True),
        MCDropout(0.3),
        layers.LSTM(64),
        MCDropout(0.3),
        layers.Dense(1)])
    model.compile(optimizer='adam', loss='mse')
    return model
model = build_bnn_model((X_train.shape[1], X_train.shape[2]))
model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=1)

mc_predictions = predict_mc(model, X_test, num_simulations=100)
mean_preds = mc_predictions.mean(axis=0).squeeze()
std_preds = mc_predictions.std(axis=0).squeeze()
# Inverse transform predictions
mean_preds_inv = scaler.inverse_transform(mean_preds.reshape(-1, 1)).squeeze()
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1)).squeeze()
std_preds_inv = std_preds * (scaler.data_max_ - scaler.data_min_)
# Evaluate performance
rmse = np.sqrt(mean_squared_error(y_test_inv, mean_preds_inv))
r2 = r2_score(y_test_inv, mean_preds_inv)
print("BNN RMSE:", rmse)
print("BNN R² Score:", r2)
# Plot predictions with uncertainty
plt.figure(figsize=(14, 6))
plt.plot(y_test_inv, label='Actual Price', color='gray')
plt.plot(mean_preds_inv, label='Predicted Mean', color='blue')
plt.fill_between(np.arange(len(mean_preds_inv)),
```

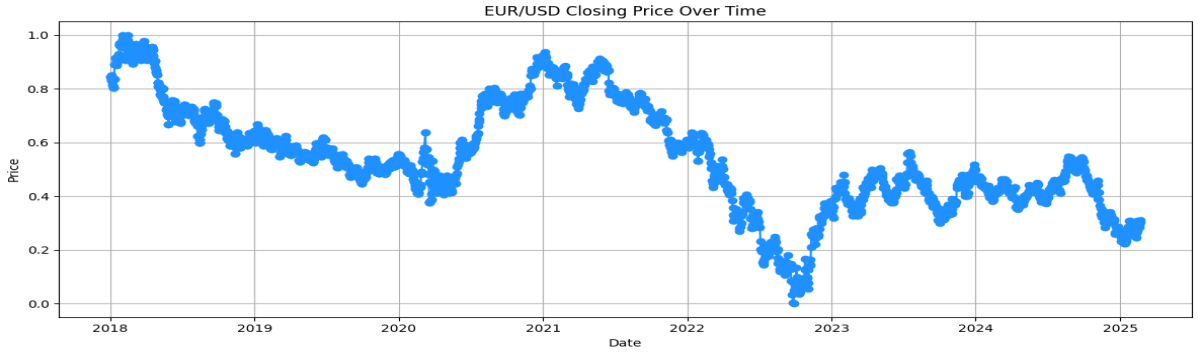
```
                mean_preds_inv - 2*std_preds_inv,
                mean_preds_inv + 2*std_preds_inv,
                color='blue', alpha=0.2, label='±2 Std Dev')
plt.title('BNN-Monte Carlo Dropout on EUR/USD Data')
plt.xlabel('Time Index')
plt.ylabel('EUR/USD Price')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
import numpy as np
import tensorflow as tf
# Function to make Monte Carlo predictions
def predict_mc(model, X, num_simulations=100):
    predictions = np.array([model(X, training=True) for _ in range(num_simulations)])
    return predictions
# Function to calculate the Confidence Score
def calculate_confidence_score(predictions):
    # Calculate the standard deviation across the simulations
    std_preds = np.std(predictions, axis=0).squeeze()
    # The confidence score can be represented by 1 - normalized std deviation
    confidence_score = 1 - (std_preds / np.max(std_preds))  # Normalize to get a value between
0 and 1
    return confidence_score
# Assuming X_test is the test data and model is the trained BNN
# Perform Monte Carlo predictions
num_simulations = 100
mc_predictions = predict_mc(model, X_test, num_simulations=num_simulations)
# Calculate the Confidence Score
confidence_scores = calculate_confidence_score(mc_predictions)
# Print the Confidence Scores
print("Confidence Scores:", confidence_scores)
```

APPENDIX-2: SCREENSHOTS









CHAPTER-9

FUTURE ENHANCEMENT

While the current hybrid framework combining LSTM, XGBoost, and Bayesian Neural Networks with Monte Carlo Dropout provides promising results for risk-sensitive trading, there is significant scope for future development. One potential enhancement is the integration of real-time data streaming and live trading environments, allowing the model to make adaptive decisions based on incoming market data. Additionally, incorporating macroeconomic indicators, news sentiment analysis, and technical signals can improve the model's context awareness and predictive accuracy.

Another promising direction is to explore Reinforcement Learning (RL) techniques to dynamically optimize trading strategies over time. Furthermore, leveraging Explainable AI (XAI) methods can help interpret model predictions and increase trust in automated trading systems. Lastly, deploying the model as a cloud-based API or mobile application would make it accessible to a broader range of users, including retail investors and financial analysts.

CHAPTER-10

CONCLUSION

In this project, we developed a robust risk prediction framework using advanced machine learning techniques to accurately assess potential risks and support data-driven decision-making. By leveraging models such as LSTM for capturing sequential trends, XGBoost for high-performance classification, and Gaussian Processes for uncertainty estimation, our hybrid approach provides both predictive accuracy and reliability.

The proposed system not only enhances the ability to foresee high-risk scenarios but also supports proactive measures to mitigate them. This predictive model is particularly valuable in dynamic environments, where early risk detection plays a crucial role in optimizing outcomes and minimizing losses. Future work may involve integrating real-time data feeds, expanding to multi-source data inputs, and refining uncertainty quantification to further improve decision support in high-stakes applications.

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