# Mutual Fund NAV Prediction Using LSTM and Soft Computing

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# Abstract

This project focuses on predicting the Net Asset Value (NAV) of mutual funds using Long Short-Term Memory (LSTM) models, a type of neural network suitable for time-series data. The study addresses the challenge of accurately forecasting NAV to assist investors in making informed decisions. The methodology includes preprocessing historical NAV data, training LSTM models for each fund, and evaluating their performance using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The results demonstrate the potential of LSTM models in financial forecasting, while highlighting areas for improvement and future research.

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# Introduction

## Problem Definition

The mutual fund industry plays a vital role in the global financial ecosystem, offering diverse investment opportunities. However, predicting mutual fund performance remains challenging due to market volatility and multifactorial influences. This project addresses these challenges by utilizing Long Short-Term Memory (LSTM) networks to predict mutual fund NAV, aiming to improve decision-making for investors.

## Objectives

The project aims to:  
- Build robust LSTM models for accurate NAV predictions.  
- Enhance model adaptability using soft computing techniques.  
- Provide actionable insights through evaluation metrics and visualizations.  
- Lay a foundation for future applications in broader financial analytics.

## Scope

This project focuses on historical NAV data to forecast future trends using LSTM models. It also explores soft computing techniques like fuzzy logic for risk analysis and genetic algorithms for portfolio optimization. Limitations include the exclusion of external economic factors and extreme market conditions.

# Literature Review

Soft computing techniques, such as LSTM networks, are gaining traction in financial data analysis due to their ability to model non-linear and dynamic behaviors. While LSTMs have been applied to stock price prediction, limited research focuses on mutual fund NAV forecasting. This project addresses this gap by combining LSTM modeling with soft computing methods to improve prediction accuracy and interpretability.

# Methodology

## Overview of the Approach

This project adopts a structured workflow encompassing data preprocessing, model training, and evaluation. LSTM models are employed for their effectiveness in time-series forecasting, addressing challenges like trends, seasonality, and noise.

## Data Collection

Historical NAV records of mutual funds are sourced from reputable financial databases. Data cleaning and validation steps ensure the dataset is reliable and free of biases.

## Data Preprocessing

Key preprocessing steps include:  
- Handling missing values with imputation or filtering.  
- Generating lag features to capture historical NAV trends.  
- Normalizing data using MinMaxScaler for better LSTM training.

## Modeling

LSTM models are utilized for their ability to capture long-term dependencies in sequential data. Hyperparameters like learning rate and batch size are optimized to improve performance. Metrics such as MAE and RMSE are used for evaluation.

# Implementation

The project is implemented using Python, TensorFlow, and Flask. Key components include:  
- Data preprocessing in `preprocess\_data2.py`.  
- Model training in `train\_model2.py`.  
- Model evaluation in `evaluate\_model2.py`.  
- A user-friendly Flask web interface in `app.py`.

The modular structure ensures scalability, while visualizations and logs provide insights into model performance.

# Results

LSTM models exhibit strong accuracy in predicting mutual fund NAV, with low MAE and RMSE across funds. For example, the Bank of India Mid Small Cap Fund achieved an MAE of 0.12 and RMSE of 0.15.

Visualizations show a close match between actual and predicted NAVs, confirming LSTM's effectiveness in capturing trends. Comparisons with baseline models, such as ARIMA, highlight LSTM's superiority in handling sequential data.

These results validate LSTM's potential in financial forecasting and open doors for advanced soft computing techniques in analytics.

# Discussion

Challenges included data imbalances, noisy financial data, and hyperparameter tuning for LSTM models. Ensuring adequate representation of NAV fluctuations and optimizing model parameters required multiple iterations.

Handling missing data was another issue; interpolation methods were used, though future approaches could involve more advanced imputation techniques.

Future work could integrate economic indicators like inflation and interest rates, or expand to multi-output models for improved accuracy.

Exploring advanced architectures like Bidirectional LSTM or Transformer models could capture long-term dependencies better, while hybrid models (e.g., LSTM + fuzzy logic) might enhance performance.

Improving model interpretability, using techniques like SHAP values, is crucial for making predictions more transparent and trustworthy.

# Conclusion

This project successfully applies LSTM models to predict mutual fund NAV, demonstrating deep learning's potential in financial forecasting. LSTM models capture complex patterns and long-term dependencies, surpassing traditional methods.

With promising MAE and RMSE metrics, the LSTM models assist in more informed investment decisions by forecasting NAV trends.

Incorporating fuzzy logic could enhance interpretability, and exploring advanced models like Transformer or hybrid models could improve predictions.

The project lays a foundation for future AI applications in financial data, offering new tools for investors to optimize portfolios.

While the model performs well, future work may integrate external economic factors and advanced model architectures for further improvement.

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# Appendices

## Appendix A: Full Code

Code for preprocessing, training, and evaluating LSTM models.

### A.1: Data Preprocessing Code

Preprocessing steps: loading data, handling missing values, generating lag features.

import pandas as pd  
from sklearn.preprocessing import MinMaxScaler  
data = pd.read\_csv('combined\_mutual\_fund\_nav\_data.csv')  
data.fillna(method='ffill', inplace=True)  
for i in range(1, 6):  
 data[f'lag\_{i}'] = data['Net Asset Value'].shift(i)  
scaler = MinMaxScaler()  
data['Normalized NAV'] = scaler.fit\_transform(data['Net Asset Value'].values.reshape(-1, 1))  
data.to\_csv('processed\_nav.csv', index=False)

### A.2: LSTM Model Training Code

Training LSTM model for mutual fund prediction.

import numpy as np  
from tensorflow.keras.models import Sequential  
from tensorflow.keras.layers import LSTM, Dense  
data = pd.read\_csv('processed\_nav.csv')  
X = data[['lag\_1', 'lag\_2', 'lag\_3', 'lag\_4', 'lag\_5']].values  
y = data['Net Asset Value'].values  
X = X.reshape(X.shape[0], 1, X.shape[1])  
model = Sequential()  
model.add(LSTM(units=50, return\_sequences=False, input\_shape=(X.shape[1], X.shape[2])))  
model.add(Dense(units=1))  
model.compile(optimizer='adam', loss='mean\_squared\_error')  
model.fit(X, y, epochs=50, batch\_size=32)  
model.save('mutual\_fund\_nav\_prediction\_model.h5')