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Hybrid Deep Learning Model for Multi-Asset Financial Market Prediction using LSTM- GRU Architecture

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Abstract - Predicting financial market trends is kind of hard because time series data is always shifting around and behaves non linearly, which makes it unpredictable. In this work we put forward a Hybrid LSTM–GRU Deep Learning setup, meant for forecasting prices of multiple assets, like shares, cryptocurrencies, foreign exchange, and even commodities. We gather past market information, then we clean it up and scale it with normalization and we also do feature engineering. For those features we lean on common technical signals such as RSI, MACD, SMA, and EMA. The hybrid method blends the long horizon memory strength of LSTM with the faster computational handling of GRU, so that the overall prediction quality is higher. After training, we judge the model using MAE, RMSE, MAPE, and R^2 Score, then we place its results next to both more traditional machine learning methods and other deep learning models. In the experiments, the hybrid design shows better forecasting accuracy and it also seems to catch those more intricate market movements, better than the alternatives. Overall, this framework can help with smarter investment decisions, portfolio oversight, and algorithmic trading, so it ends up being a workable approach for today's financial forecasting tasks.

Keywords: Financial Market Prediction, Hybrid LSTM-GRU, Deep Learning, Time-Series Forecasting, Technical Indicators, Artificial Intelligence, Machine Learning.

PROPOSED METHODOLOGY

6.1 Introduction

The proposed methodology is basically gives a framework for trying to forecast financial market prices with a hybrid deep learning architecture, it mixes Long Short-Term Memory (LSTM) together with Gated Recurrent Unit (GRU) networks. Financial time-series data are known for volatility, nonlinear patterns, and this temporal dependency thing, so prediction is not that easy. To handle those aspects, the approach brings in historical market data preprocessing, some feature engineering, then sequence creation, next the hybrid model training and after that a performance evaluation. The workflow consists of six major phases:

1. Historical Data Collection
2. Data Preprocessing
3. Feature Engineering
4. Hybrid LSTM–GRU Model Development
5. Prediction
6. Performance Evaluation

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Figure 6.1 Proposed Research Framework

```
Historical Market Data
        │
        ▼
Data Collection Module
        │
        ▼
Data Cleaning & Validation
        │
        ▼
Feature Engineering
        │
        ▼
Sequence Generation (60 Days)
        │
        ▼
Hybrid LSTM Layer
        │
        ▼
GRU Layer
        │
        ▼
Dense Layer
        │
        ▼
Price Prediction
        │
        ▼
Performance Evaluation
```

Figure 6.1: Overall methodology for the proposed forecasting system.

6.2 Data Collection

Historical market data are collected from publicly available financial data providers such as Yahoo Finance. Each record contains Open, High, Low, Close, and Volume values.

Table 6.1 Dataset Description

Attribute	Description	Data Type
Date	Trading Day	Date
Open	Opening Price	Float
High	Highest Price	Float
Low	Lowest Price	Float
Close	Closing Price	Float
Volume	Trading Volume	Integer

6.3 Data Preprocessing

Raw financial data sets often have missing observations, duplicated entries, or weird scale

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differences, like sometimes numbers are all over the place. Before training, preprocessing helps, and yes it basically makes things cleaner.

In the preprocessing flow you’ll usually see things like, Missing value removal, Duplicate removal, and Data validation. After that, they do Min–Max normalization, then there is this step for sequence generation, where you turn the raw rows into ordered chunks for the model.

Normalization Formula
X′=X−XminXmax−XminX'=\frac{X-X_{min}}{X_{max}-X_{min}}X′=Xmax−XminX−Xmin

where XXX is the original value, XminX_{min}Xmin and XmaxX_{max}Xmax are the minimum and maximum values of the feature.

Figure 6.2 Data Preprocessing Flow

```
Raw Dataset
   |
   ▼
Missing Value Removal
   |
   ▼
Duplicate Removal
   |
   ▼
Normalization
   |
   ▼
Sequence Generation
   |
   ▼
Training Dataset
```

Table 6.2 Preprocessing Activities

Activity	Purpose
Missing Value Handling	Improve data completeness
Duplicate Removal	Eliminate redundant records
Normalization	Standardize feature scales
Sequence Generation	Prepare time-series inputs

6.4 Feature Engineering

Feature engineering enhances the predictive capability of the model by combining raw market variables with derived indicators.

Table 6.3 Input Features

Feature	Description
Open	Opening price
High	Highest price
Low	Lowest price
Close	Closing price
Volume	Trading volume
SMA	Simple Moving Average
EMA	Exponential Moving Average
RSI	Relative Strength Index
MACD	Moving Average Convergence Divergence

Figure 6.3 Feature Engineering Process

```
Historical Prices
       │
       ▼
Technical Indicators
       │
       ▼
Feature Selection
       │
       ▼
Training Dataset
```

6.5 Hybrid LSTM–GRU Architecture

So, the forecasting model uses both LSTM and GRU bits. The LSTM part, helps it hold onto long- term ties in sequence like data, and it kind of keeps the context. Then the GRU layer comes in, and it lowers the computational load, plus it makes the training converge faster, maybe with less fuss.

After that there’s a Dense output layer that spits out the forecasted closing price.

Table 6.4 Network Configuration

Layer	Units	Activation
LSTM	64	tanh
GRU	32	tanh
Dense	1	Linear

Figure 6.4 Hybrid Network

```
   Input Sequence
         │
         ▼
+-----------------+
|   LSTM Layer    |
+-----------------+
         │
         ▼
```

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```
+----------------+
|    GRU Layer   |
+----------------+
        |
        ▼
+----------------+
| Dense Layer   |
+----------------+
        |
        ▼
Predicted Price
```

6.6 Model Training

The normalized sequences are divided into training and testing sets. The model is trained using the Adam optimizer and Mean Squared Error (MSE) loss function. Hyper parameters such as learning rate, batch size, and number of epochs are selected through preliminary experiments.

Table 6.5 Training Parameters

Parameter	**Value**
Epochs	20
Batch Size	32
Optimizer	Adam
Loss Function	Mean Squared Error
Sequence Length	60 Days

6.7 Performance Evaluation

The trained model is evaluated using standard regression metrics.

Table 6.6 Evaluation Metrics

Metric	**Formula**	**Purpose**
MAE	Mean Absolute Error	Average prediction error
RMSE	Root Mean Square Error	Penalizes larger errors
MAPE	Mean Absolute Percentage Error	Relative prediction error
R^2 Score	Coefficient of Determination	Goodness of fit

6.8 Algorithm

I collected historical financial data first. Missing and duplicate records were removed after that. Normalization was applied to the dataset so the values would sit on a similar scale. Time series sequences came from there.

The hybrid LSTM GRU model got built next. Training used the training dataset. Predictions for future prices were then made with the testing dataset. Evaluation relied on MAE RMSE MAPE and R squared but some of the numbers felt stronger than others. I am not totally sure if that means the model handled everything evenly.

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6.9 Chapter Summary

The proposed method for multi asset market prediction was laid out in this chapter. It mixes preprocessing with feature engineering and a hybrid LSTM GRU model to work with time patterns in the data.

That part feels like the core of it. The workflow tries to push accuracy higher and help with decisions but some details on how it all fits together still seem unclear in places.

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