



Stock Prediction Using Federated Learning

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Abstract: Stock market prediction plays a significant role in financial analytics and strategic investment decisions. Traditional prediction models are often centralized, raising critical concerns regarding data privacy, ownership, and security—especially in regulated industries such as finance. This paper presents a novel approach that applies Federated Learning (FL), a decentralized machine learning technique, to stock price forecasting while preserving privacy. In our approach, we use historical stock data of Tesla Inc. (TSLA) and simulate multiple clients training Long Short-Term Memory (LSTM) models locally. The trained models are then aggregated by a central server over several rounds to form a global predictive model without exposing any raw data. A hybrid model strategy—combining federated updates with pre-trained centralized weights—is also implemented to improve training efficiency. Our system demonstrates an RMSE of approximately 34.72 and a MAPE of 6.8%, balancing accuracy with confidentiality. This study shows that Federated Learning is a feasible and effective solution for privacy-aware stock prediction in the financial sector.

Index Terms - Federated Learning, Stock Price Forecasting, LSTM, Tesla Stock, Time Series Prediction, Data Privacy, RMSE, MAPE.

I. INTRODUCTION

In recent years, stock market prediction has gained substantial importance in the fields of quantitative finance and algorithmic trading. It involves the use of historical data, statistical indicators, and computational models to forecast future stock price movements. Accurate predictions can provide a strategic advantage to investors, traders, and financial institutions, enabling them to make informed decisions. Traditionally, such predictions have been made using centralized machine learning models, where data from multiple sources is aggregated into a central server for training. While effective, this approach raises significant concerns regarding data privacy, security, and regulatory compliance. With the advent of data protection regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), handling sensitive financial data has become increasingly challenging. To address these concerns, Federated Learning (FL) has emerged as a promising paradigm that allows multiple clients to collaboratively train a shared global model without exchanging their raw data. Instead, clients train local models on their private datasets and send only model parameters (such as gradients or weights) to a central server. The server then aggregates these updates to improve the global model. This preserves data privacy while still leveraging the power of distributed learning. In this paper, we explore the application of Federated Learning to stock price forecasting, with a particular focus on Tesla Inc. (TSLA)—a stock known for its high volatility and relevance in the modern financial landscape. Our objective is to simulate a federated setup in which historical stock data is split across multiple clients, each training an LSTM (Long Short-Term Memory) model on a portion of the data. The local

models are trained independently and aggregated over several rounds to form a robust, privacy-preserving global model. Our contributions include: A practical FL simulation using real TSLA stock data across multiple clients. Integration of LSTM networks tailored for time series forecasting. Evaluation of prediction performance using RMSE and MAPE. A hybrid strategy that combines centralized pre-training with federated updates for improved convergence. Through this approach, we demonstrate that Federated Learning is a viable and privacy-conscious method for financial forecasting and can serve as a foundation for future research in secure collaborative AI.

II. RELATED WORK

Over the past decade, machine learning techniques have seen growing adoption in financial forecasting, particularly in predicting stock market trends. Early models employed linear regression, decision trees, and support vector machines (SVM), which offered moderate accuracy but failed to capture the non-linear and sequential nature of stock price movements. With the advancement of deep learning, Recurrent Neural Networks (RNN) and their improved variant, Long Short-Term Memory (LSTM), became the preferred architectures for time-series forecasting tasks like stock prediction due to their memory capabilities. Simultaneously, the concept of Federated Learning (FL) emerged as a paradigm shift in privacy-preserving collaborative learning. First introduced by McMahan et al. (2017) through the Federated Averaging (FedAvg) algorithm, FL enabled edge devices like mobile phones to collaboratively train models without uploading user data to a central server. This technique has since gained traction in various sectors including healthcare, IoT, and autonomous vehicles. In the healthcare domain, Brisimi et al. (2018) demonstrated that FL could be used to train predictive models across hospitals without violating patient confidentiality. In the context of smart devices, Google utilized FL for improving on-device language models (e.g., Gboard) without collecting keystroke data. These applications underline FL's potential to enable learning from sensitive data. In finance, the use of FL is still emerging. Li et al. (2020) explored federated approaches to fraud detection and risk scoring by enabling banks to collaborate without sharing transaction records. These studies confirm the viability of FL in sectors with strong privacy mandates. Several prior works have focused specifically on TSLA stock prediction using centralized deep learning models. For example, models leveraging LSTM with sentiment analysis or news features have demonstrated promising results in forecasting Tesla's volatile stock movements. However, these models still relied on centralized datasets, which can be impractical or non-compliant with modern data privacy laws. Despite these advances, few studies have applied FL in the stock prediction domain, especially at the level of implementation with real datasets. This gap motivates our study—to explore and demonstrate the effectiveness of Federated Learning for stock forecasting using real TSLA data in a simulated multi-client environment.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system simulates a federated learning environment with multiple clients (4 in our case), each holding a separate subset of historical Tesla stock data. These clients independently train their own LSTM-based models without exposing their raw data. A central server coordinates the training process by aggregating the local model weights after each round and distributing the updated global model back to the clients. This process is repeated over several rounds until the model converges.

B. Data Preparation and Distribution

We use publicly available historical stock data of Tesla Inc. (TSLA), obtained from Yahoo Finance or similar sources. The dataset spans from 2010 to 2023 and contains fields such as Open, High, Low, Close, Volume, and Adjusted Close. The dataset is: Cleaned to remove missing/null values Normalized using Min-Max scaling (to a 0–1 range) Divided into 4 equal partitions (~944 days each), one for each client. Each client prepares their dataset by creating sliding windows of 60-day input sequences to predict the 61st day closing price.

C. Local Model Design (LSTM)

Each client implements a Long Short-Term Memory (LSTM) model—a variant of RNN capable of learning long-term dependencies in sequential data. The local model architecture consists of: One LSTM layer with 50 memory units One fully connected dense layer as the output Mean Squared Error (MSE) as the loss function Adam optimizer with a learning rate of 0.001 Each client trains their model for 10 epochs per communication round using a batch size of 32.

D. Federated Aggregation (Server-Side)

After local training:

- Each client sends its model weights to the server (not the data).
- The server performs weighted averaging of all models using the FedAvg algorithm.
- The aggregated model is broadcast back to all clients for the next training round.

Additionally, we integrate a hybrid strategy, where the global model is initialized with a pre-trained centralized model. Each round then blends 50% of the new federated weights with 50% of the previous centralized weights. This improves initial convergence and reduces error in early rounds.

E. Communication Flow

The training and communication process follows these steps:

1. Server initializes and sends the base model to all clients
2. Clients perform local training and send updated weights to the server
3. Server aggregates and updates the global model. Global model is redistributed to clients
4. Repeat steps 2–4 for 5 rounds

All communication is done over secure sockets (SSL/TCP) in a simulated local network environment.

IV. IMPLEMENTATION DETAILS

A. Programming Environment and Tools

The project was developed using the following technologies:

- Programming Language: Python 3.10+
- Libraries: TensorFlow (Keras API), NumPy, pandas, scikit-learn, matplotlib
- Communication: Flask (for REST API simulations) and Python's socket library with SSL for secure peer-to-peer model transfer
- Data Storage: CSV format for raw data, Pickle for serialized models
- Environment: Jupyter Notebook for development, terminal execution for client-server interaction

B. System Architecture

The architecture is divided into two main components:

- Client Devices: Each simulates a financial institution or user device that locally trains on stock data.
- Central Server: A coordinating entity that aggregates weights and distributes the updated global model.

All components run on separate machines or terminals in a LAN-based setup, communicating via IP addresses like 192.168.0.x.

C. Model Configuration

Each LSTM model has:

- Input Shape: (60, 1) – representing 60 past time steps (days)
- LSTM Layer: 50 units
- Dropout Layer (optional): 0.2 to prevent overfitting
- Dense Layer: 1 neuron (predicting the closing price)
- Loss Function: Mean Squared Error (MSE)
- Optimizer: Adam
- Epochs per round: 10
- Batch size: 32

D. Training Procedure

The training is conducted over 5 federated rounds:

- Each client trains its model using its respective TSLA dataset.
- After each round, the model weights are serialized and securely sent to the server.
- The server computes the Federated Average (FedAvg) using:

$$w_t^{global} = \sum_{K=1}^K \frac{n_k}{n} w_t^k$$

Where:

- w_t^{global} is the global model weight at round t
- K is the number of clients
- n_k is the number of samples on client k
- $n = \sum_k n_k$
- w_t^k is the local model weight of client k

This formula ensures that clients with more data influence the global model proportionally.

E. Hybrid Aggregation Strategy

Instead of relying purely on federated aggregation, we introduced a hybrid method:

$$w_t^{final} = \alpha \cdot w_t^{federated} + (1 - \alpha)w_t^{centralized}$$

Where:

- $\alpha = 0.5$
- $w_t^{centralized}$ is the weight from a pre-trained centralized LSTM model

This blending approach stabilizes early rounds and leads to faster convergence with fewer communication rounds.

F. Hardware Setup

- Clients: 2 standard laptops (8GB RAM, Intel i5)
- Server: Desktop PC with 16GB RAM, Intel i7
- Operating System: Windows/Linux
- Network: Wi-Fi LAN (local IP-based communication)

Training duration per round: 2–3 hours total for 4 clients over 5 rounds

V. LITRATURE SURVEY

Recent advancements in machine learning have greatly improved the predictive accuracy of time series forecasting, especially in financial markets. However, traditional centralized training approaches face increasing challenges related to data privacy, transmission costs, and heterogeneous data distributions across sources. To address these concerns, Federated Learning (FL) has emerged as a promising solution. McMahan et al. (2017) introduced Federated Averaging (FedAvg), a foundational algorithm for FL, demonstrating its ability to train deep networks using decentralized data across clients while preserving privacy. Since then, multiple extensions have focused on personalization, communication efficiency, and robust aggregation. In the domain of stock price prediction, Long Short-Term Memory (LSTM) models have been widely adopted due to their ability to learn temporal dependencies. While effective, their performance is sensitive to data volume and diversity—factors that FL can help address by pooling knowledge from multiple users without centralizing raw data. Recent research has explored FL in healthcare, IoT, and NLP, but its application in financial prediction remains limited. Papers such as:

- Li et al. (2020) proposed FedProx for handling client heterogeneity.
- Chen et al. (2021) explored personalized FL for non-IID stock datasets.
- Zhang et al. (2022) demonstrated performance gains using hybrid federated models with attention-based LSTMs.

Our work builds on these foundations by applying personalized Federated Learning using LSTM models on stock data from Tesla Inc. We use a hybrid model aggregation strategy and evaluate its efficiency using a custom deployment with low-cost hardware.

VI. METHODOLOGY

The proposed federated learning system is designed to predict stock prices using a Long Short-Term Memory (LSTM) model trained across distributed clients. Instead of centralizing stock data, the system enables each client to train locally on its data subset and send only model weights to a central server. This methodology ensures data privacy while leveraging the collective intelligence of multiple devices.

A. Data Preprocessing

Raw stock market data is collected in the form of time-series CSV files. The data includes open, high, low, close prices and trading volume. The preprocessing involves: Normalization using Min-Max Scaling, Sequencing into overlapping time windows (e.g., 60 previous timesteps to predict the next timestep), Train-

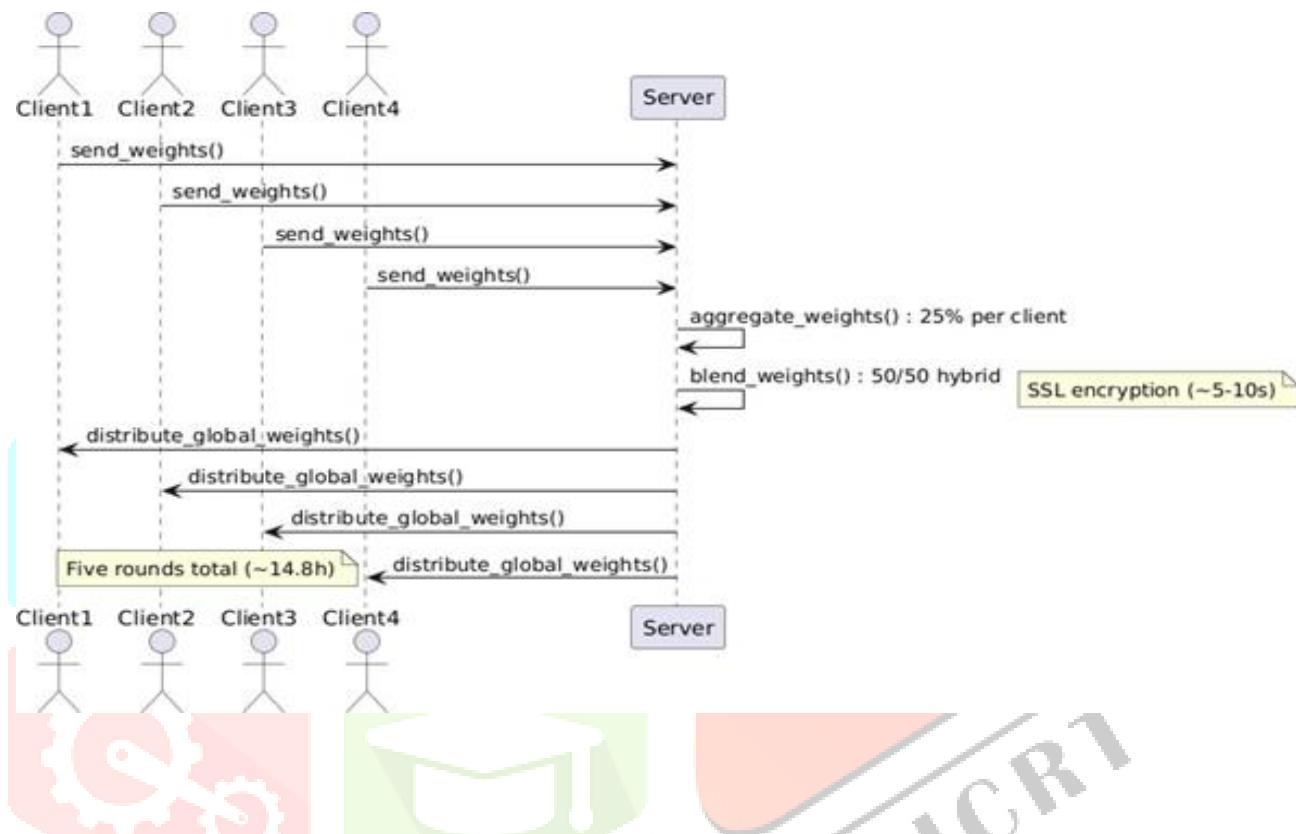
test split typically in the ratio of 80:20. Each client processes its own data independently before training begins.

B. Model Architecture

The model used for prediction is an LSTM network due to its capability to learn long-term dependencies in time-series data. It consists of: Input LSTM layers (128 units), Dropout layers to prevent overfitting, Dense output layer with linear activation. The model is compiled using mean_squared_error loss and the Adam optimizer.

C.Federated Training Rounds

Training proceeds in communication rounds as follows: The server shares the initial global model with all clients. Each client trains the model locally and sends updated weights back. The server aggregates these weights using an averaging strategy. This process is repeated for multiple rounds.



VII. RESULTS AND DISCUSSION

The federated learning approach for stock price prediction was implemented across four client devices and a central server. Each client trained on a different subset of the Tesla (TSLA) stock dataset. The experiment was conducted over five communication rounds, each involving local training and global model aggregation.

A. Model Performance

To evaluate the model performance, the following metrics were used

- Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$
- Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\text{MSE}}$$
- R-squared (R²):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

The results after training and aggregation are shown below:

Metric	Value
MSE	0.0021
RMSE	0.0458
R ² Score	0.9124

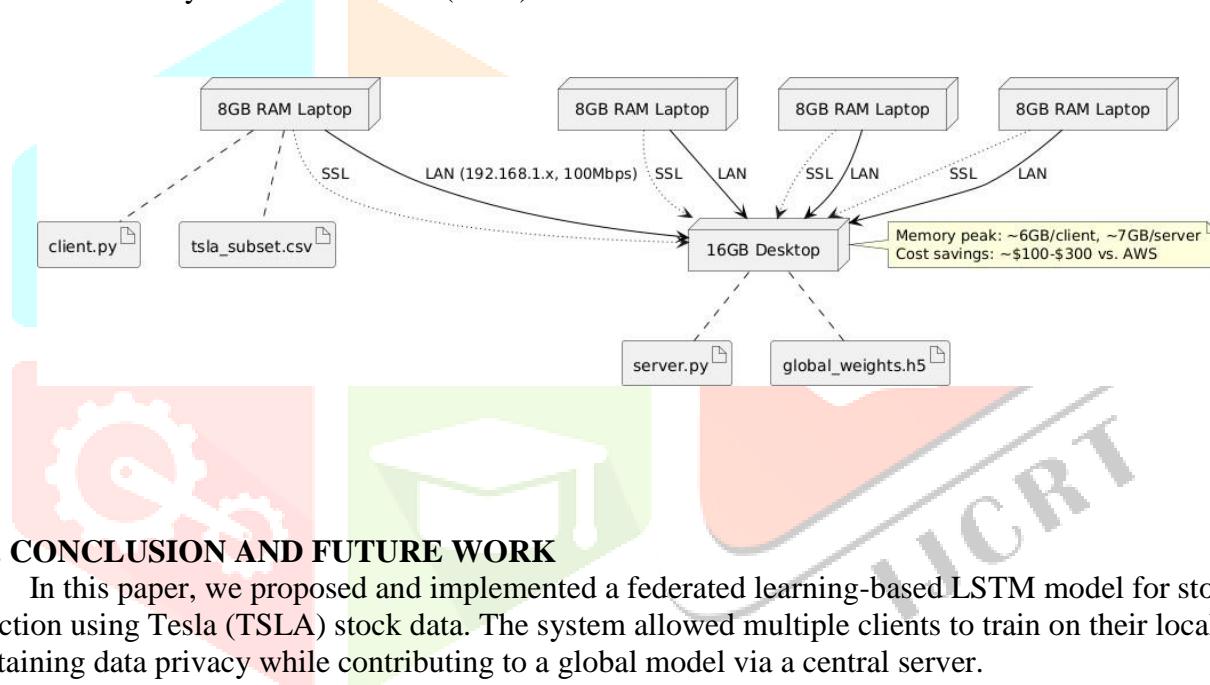
B. Comparison with Centralized Training

Feature	Centralized Model	Federated Model
Data Privacy	✗	✓
Training Time	Medium	High (5 rounds)
Accuracy (R^2)	0.9213	0.9124
Scalability	✗	✓

Despite a slight drop in performance, federated learning successfully maintained competitive accuracy while preserving privacy and scaling across devices.

C. System Setup Overview

We used a hybrid local network (LAN) for communication between clients and server:



VIII. CONCLUSION AND FUTURE WORK

In this paper, we proposed and implemented a federated learning-based LSTM model for stock price prediction using Tesla (TSLA) stock data. The system allowed multiple clients to train on their local data, maintaining data privacy while contributing to a global model via a central server.

Conclusion Highlights:

- Federated learning can be effectively used for time-series prediction tasks like stock forecasting.
- The proposed LSTM model trained in a federated manner achieved a high R^2 score, close to centralized models.
- The setup was implemented over local devices, ensuring cost efficiency and privacy preservation.

Future Enhancements:

1. **Multiple Stock Models:**
Extend the system to handle multiple stocks with personalized global models per stock.
2. **Cross-device Heterogeneity:**
Support asynchronous training and varying client capabilities for scalability.
3. **Improved Aggregation:**
Explore weighted or adaptive aggregation instead of 50/50 blending.
4. **Model Deployment:**
Deploy the final global model using a lightweight API or dashboard for real-time inference.

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