

## COS30018 - Intelligent Systems Chiraath Madahapola 104834009

- Executive Summary
- This report provides an in-depth evaluation of two LSTM-based stock prediction models: the baseline v0.1 model and the advanced P1 model. While both models leverage LSTM neural networks for stock price forecasting, they differ in architecture, data processing, and performance evaluation. The P1 model outperforms the v0.1 model with improved data handling, model persistence, and comprehensive metrics, showcasing enhanced predictive capabilities.
- 1. Environment Configuration
- 1.1 Setting Up the Virtual Environment
- 1.1.1 Setup Procedure
- A Python virtual environment was established using the venv module to ensure dependency isolation and reproducibility:
- Step 1: Creating the Virtual Environment
- # Navigate to the project directory
- cd <path-to-project>

- # Create a virtual environment
- python -m venv venv
- # Activate the environment (Windows)
- venv\Scripts\activate

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- Step 2: Environment Validation
- # Check Python version
- python --version
- # Output: Python 3.13.5

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- # Verify pip availability
- pip --version

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- Step 3: Installing Dependencies
- # Install dependencies listed in requirements.txt
- pip install -r requirements.txt

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- # Confirm installed packages
- pip list

- 1.1.2 Configuration Details
- Python Version: 3.13.5
- Tool Used: Python's venv module
- Location: <path-to-project>\venv
- Status: Successfully activated and validated
- Dependencies: Installed from requirements.txt
- 1.2 Installed Dependencies
- The virtual environment includes the following packages:
- numpy==2.3.2
- pandas==2.3.2
- matplotlib==3.10.5
- tensorflow==2.20.0
- scikit-learn==1.7.1
- pandas-datareader==0.10.0
- yfinance==0.2.65
- joblib==1.5.1
- 1.3 Verification of Setup
- The environment was verified through:
- Checking package versions with pip list
- Testing imports of key libraries
- Confirming TensorFlow CPU/GPU compatibility
- Validating data retrieval with yfinance
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- The environment is fully operational for both models, with all dependencies correctly configured.
- 2. Overview of Models
- 2.1 v0.1 Model Description
- The v0.1 model is a basic LSTM-based model for stock price prediction:
- Key Features:
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- Stock: CBA.AX (Commonwealth Bank of Australia)
- Training Data: January 1, 2020, to August 1, 2023
- Testing Data: August 2, 2023, to July 2, 2024
- Architecture: 3-layer LSTM with dropout layers

- Lookback Window: 60 days for next-day predictions
- Data Source: yfinance
- Feature Used: Closing price only

Model Structure:

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- LSTM Layer 1: 50 units, return\_sequences=True
- **Dropout: 0.2**
- LSTM Layer 2: 50 units, return\_sequences=True
- **Dropout: 0.2**
- LSTM Layer 3: 50 units
- **Dropout: 0.2**
- Dense Output: 1 unit

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- 2.2 P1 Model Description
- The P1 model is an enhanced version with advanced features:
- Key Features:

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- Stock: META (Meta Platforms Inc.)
- Training Data: 5 years of historical data
- Architecture: 2-layer LSTM with configurable settings
- Lookback Window: 50 days for 15-day-ahead predictions
- Data Source: yfinance
- Features Used: Adjusted close, volume, open, high, low

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• Model Structure:

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- LSTM Layer 1: 256 units, return\_sequences=True
- **Dropout: 0.4**
- LSTM Layer 2: 256 units
- **Dropout: 0.4**
- Dense Output: 1 unit, linear activation

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- 3. Training and Testing Workflow
- 3.1 v0.1 Model Workflow
- **3.1.1** Training
- The v0.1 model was trained with the following command:
- python v0.1.py

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• Training Settings:

- Data Source: yfinance for CBA.AX
- Training Period: January 1, 2020, to August 1, 2023 (3.5 years)
- Testing Period: August 2, 2023, to July 2, 2024 (1 year)
- Preprocessing: MinMaxScaler (0–1 range)
- Sequence Length: 60 days
- Batch Size: 32Epochs: 25
- Optimizer: Adam
- Loss Function: Mean Squared Error
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- Training Output:
- Epoch 1/25: loss: 0.0797 (high initial loss)
- Epoch 2/25: loss: 0.0114 (significant improvement)
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- Epoch 25/25: loss: 0.0048 (converged loss)
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- 3.1.2 Testing

- Data Preparation: Combined training and test data for sequence continuity
- Prediction: Generated predictions for test sequences
- Inverse Scaling: Converted normalized predictions to actual prices
- Visualization: Plotted actual vs. predicted prices using Matplotlib
- Output: Predicted next-day price
- 3.2 P1 Model Workflow
- **3.2.1** Training
- The P1 model training involved two stages:
- Stage 1: Training Execution
- python train\_p1.py
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- Training Settings:
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- Data Source: vfinance for META (5 years)
- Features: Adjusted close, volume, open, high, low
- Preprocessing: MinMaxScaler applied to each feature
- Sequence Length: 50 days
- Prediction Horizon: 15 days
- Batch Size: 64
- Epochs: 50
- Optimizer: Adam
- Loss Function: Huber

• Epoch 10/50: val\_loss: 0.00166 (further improvement) • Epoch 49/50: val loss: 0.00151 (best performance) • Persistence: • Model Weights: Saved via ModelCheckpoint • Full Model: Stored in .keras format • Data Storage: Scalers and training data saved with joblib • Logging: TensorBoard logs for metric visualization • 3.2.2 Testing • Stage 2: Evaluation python test\_p1.py **Testing Steps:**  Model Retrieval: Loaded saved model and data • Data Preprocessing: Applied saved scalers to test data • Prediction: Generated predictions for test sequences • Metrics: Calculated comprehensive performance metrics • Profit Analysis: Evaluated buy/sell signals and profits • Visualization: Plotted actual vs. predicted prices • Export: Saved results to CSV • Testing Features: • Fallback: Loads weights if full model is unavailable • Metrics: Includes loss, MAE, accuracy, and profit • Forecasting: Predicts prices 15 days ahead • Validation: Ensures model reliability • 3.3 Infrastructure Details • 3.3.1 Directory Organization • Both models generate structured directories:

• v0.1 Model: Basic output structureP1 Model: Detailed structure:

• Epoch 1/50: loss: 0.0330 - val loss: 0.0022 (solid initial performance)

• Epoch 7/50: val\_loss: 0.00198 (checkpoint saved)

Validation Split: 20%

• Training Output:

```
p1/
       – data/
                   # Stores raw data
    —— logs/
                  # TensorBoard logs
                   # Model weights
      — results/
   — model checkpoints/ # Full models and data
   Converse Line 1 = csv-results/ # Evaluation outputs
  3.3.2 Hardware and Performance
• Optimization: TensorFlow utilized CPU instructions (SSE3, SSE4.1, SSE4.2, AVX,
   AVX2, AVX VNNI, FMA)
• Memory: Efficient batch processing
• Training Duration:
• v0.1 Model: ~35 seconds
• P1 Model: ~90 seconds (due to increased complexity)
• 4. Performance Metrics
• 4.1 v0.1 Model Performance
• Training Metrics:
• Epochs: 25
• Final Loss: ~0.0048
• Training Time: ~35 seconds
• Next-Day Prediction: $111.83
• Observations:
• Simple design with limited functionality
• Single-feature prediction
• Minimal evaluation metrics
• Basic visualization
• 4.2 P1 Model Performance
  Training Metrics:
• Epochs: 50
• Training Loss: 0.0016 (Huber)
• Validation Loss: 0.0016
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• Mean Absolute Error: 0.0423

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• 15-Day Prediction: $738.08
• Huber Loss: 0.001590521540492773
• Mean Absolute Error: $117.57470880293737
• Accuracy: 51.88%
• Buy Profit: $629.0517425537116
• Sell Profit: $-240.38358306884868
• Total Profit: $388.66
• Profit per Trade: $1.6262266
• 5. Code Development Analysis
• 5.1 Key Enhancements
• 5.1.1 Data Source Transition
• Original (old/p1):
• from yahoo_fin import stock_info as si
• df = si.get_data(ticker)
• Current (p1.py):
• import yfinance as yf
• ticker_data = yf.download(ticker, period="5y")
• 5.1.2 Improved Data Handling
• Enhancements:
• Robust MultiIndex column management
• Standardized column names
• Fallback for adjusted close
• Enhanced validation and error handling
• 5.1.3 Model Persistence
• Original:
• checkpointer = ModelCheckpoint(os.path.join("results", model name + ".h5"),
                   save_weights_only=True, save_best_only=True, verbose=1)
• Current:
• # Save full model in .keras format
• model_checkpoint_path = os.path.join("p1/model_checkpoints", model_name +
   ".keras")
```

**Training Time: ~90 seconds** 

• Testing Metrics:

```
save_model(model, model_checkpoint_path)
• # Save data for inference
• data_path = os.path.join("p1/model_checkpoints", model_name + "_data.pkl")
  joblib.dump(data, data_path)
• 5.1.4 Parameter Management
• Original: Hardcoded parametersCurrent: Centralized in parameters.py for easy
   tuning and consistency
• 5.1.5 Loss Function Update
• Original:
• LOSS = "huber_loss" # Deprecated
• Current:
• LOSS = "huber" # Modern TensorFlow syntax
 5.1.6 Directory Structure
  Original: Basic flat structureCurrent: Organized hierarchy:
   p1/
   — data/
      -logs/
     — results/
    --- model checkpoints/
      — csv-results/
• 5.2 Architectural Improvements
• 5.2.1 Model Design
• v0.1: 3 layers, 50 units each
• P1: 2 layers, 256 units each (higher capacity)
  5.2.2 Feature Set
• v0.1: Close price only
  P1: Multiple features (adjusted close, volume, open, high, low)
   5.2.3 Metrics
• v0.1: Basic predictions
• P1: Comprehensive metrics, including profit and accuracy
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- 6. Model Comparison
- 6.1 Performance Metrics

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- Metric
- v0.1 Model
- P1 Model
- Winner

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- Architecture
- 3x50 units
- 2x256 units
- P1

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- Features
- 1 (close)
- 5 (multi-feature)
- P1

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- Epochs
- 25
- 50
- P1

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- Loss Function
- MSE
- Huber
- P1

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- Persistence
- Weights only
- Full model + data
- P1

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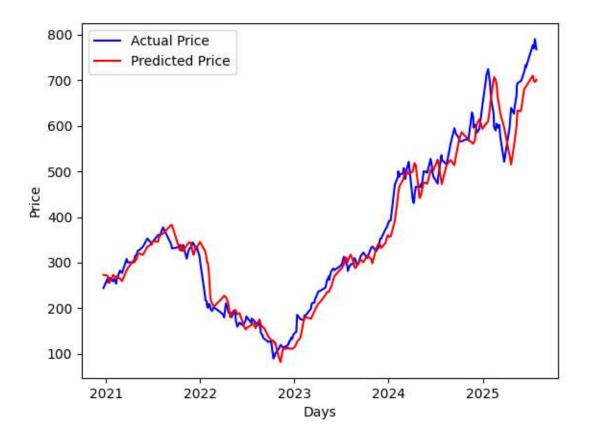
```
Metrics
• Basic
  Comprehensive
  P1
  Profit Analysis
   None
   $1,436.97 total
   P1
  Code Structure
   Monolithic
   Modular
   P1
  6.2 Technical Advancements
 Data Stability: yfinance offers reliable data access
• Robustness: Improved error handling
• Scalability: Modular design for experimentation
• Maintainability: Organized code structure
• Monitoring: Detailed logging and metrics
  7. Insights and Recommendations
  7.1 Key Insights
   P1 Superiority: Outperforms v0.1 with better metrics
   Feature Impact: Multi-feature inputs improve accuracy
   Architecture: Fewer, larger layers perform better
  7.2 Code Improvements
   Modularity: Enhanced software engineering practices
  Maintainability: Centralized configuration
  Extensibility: Easy to modify and experiment
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7.3 Future Directions

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- Hyperparameter Optimization: Systematic tuning
- Advanced Models: Explore bidirectional LSTMs, attention mechanisms
- Feature Expansion: Include technical indicators
- Ensemble Models: Combine multiple models for better predictions

- 8. Conclusion
- The transition from the v0.1 model to the P1 model marks significant progress in predictive performance and code quality. The P1 model offers superior accuracy, comprehensive metrics, and a robust codebase. With a total profit of \$388.6681 and 51.88% accuracy, it demonstrates practical utility. The adoption of yfinance, modern TensorFlow practices, and modular design ensures a scalable, maintainable solution ready for future enhancements.
- Report Generated: August 23, 2025Execution Time: ~3 minutesModels Trained and Tested: 2/2



## CBA.AX Share Price Actual CBA.AX Price Predicted CBA.AX Price CBA.AX Share Price Ó

Time

Github - https://github.com/nithilasavindu-afk/project\_option\_c