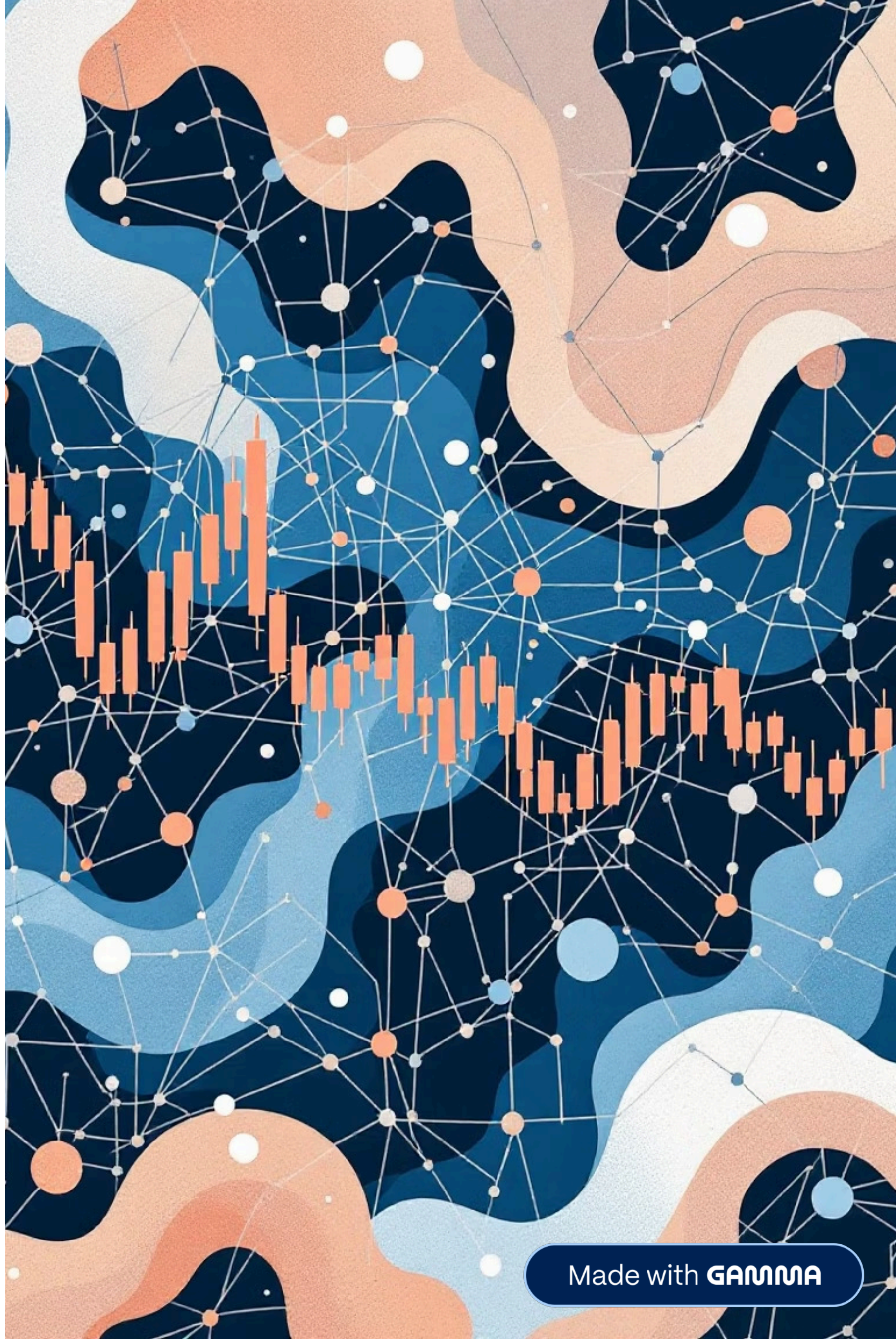
Intelligent Stock Market Prediction Using BERT Fine-Tuning and LSTM Deep Learning

CSYE 7280 – User Experience Design & Testing (Fall 2025)

Nithin Yash Menezes

This project integrates Natural Language Processing and Deep Learning to predict stock market movements, bridging technical AI modeling with user experience interpretability.



Project Overview

Goal

Develop a hybrid system combining BERT for text sentiment analysis and LSTM for price prediction to model complex stock market behavior.

Our Approach

- Fine-tune **BERT-base-cased** on financial tweet sentiment data
- Train **LSTM networks** on AAPL closing prices from Yahoo Finance
- Correlate emotional tone from social data with numerical price trends

Key Outcome: A robust, interpretable pipeline that predicts both market sentiment and stock trajectory with high accuracy.

Motivation & Relevance

Sentiment Drives Markets

Market sentiment from tweets, news, and discussions directly affects stock volatility and investor behavior.

Traditional Model Gaps

Conventional models rely purely on numeric indicators and miss crucial psychological context from social signals.

Bridging Two Worlds

This project combines linguistic intelligence (BERT) with temporal forecasting (LSTM) for holistic prediction.

UX Connection: Visual insights and interpretable results enhance decision-making capabilities for traders and analysts, transforming complex data into actionable intelligence.

Dataset Preparation

Data Sources

🧾 Hugging Face

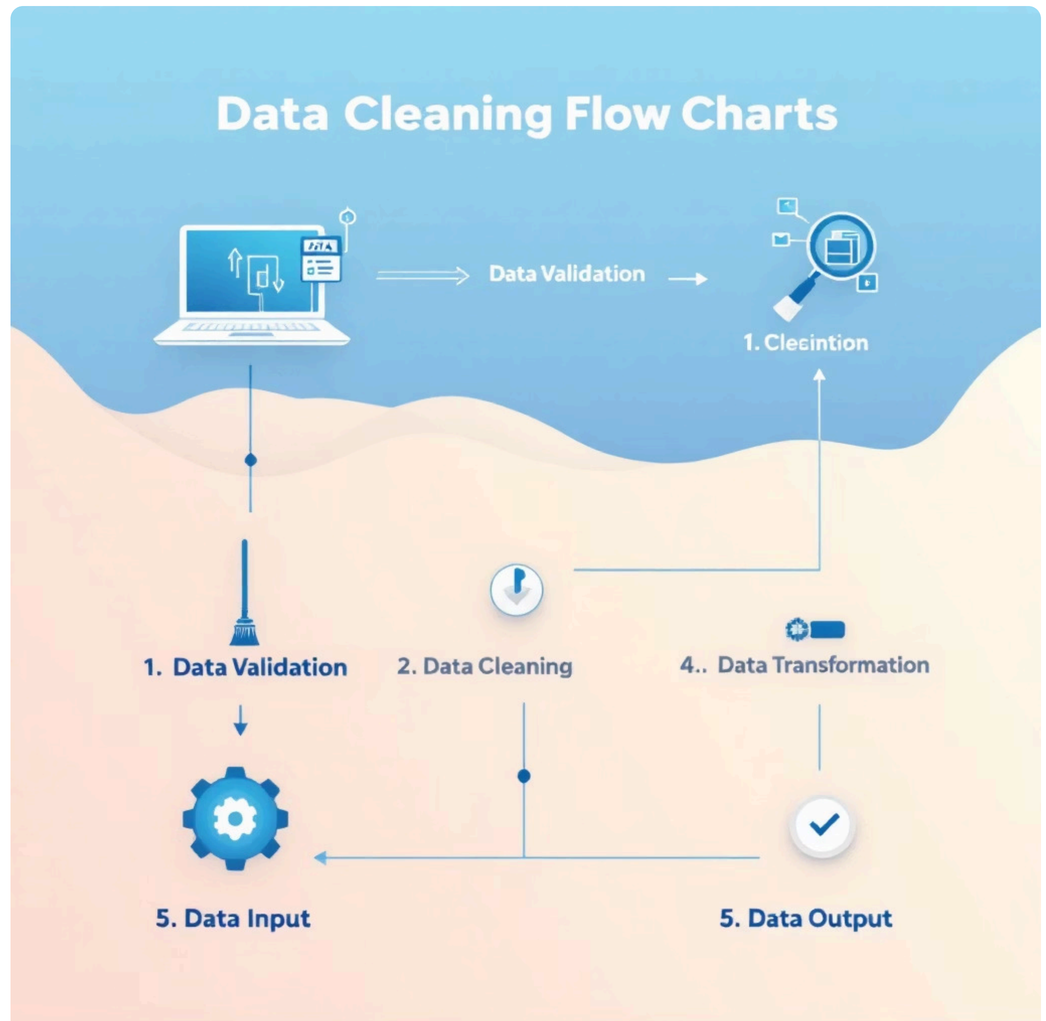
StephanAkkerman/stock-market-tweets-data — Financial sentiment classification dataset with labeled positive and negative tweets.

💹 Yahoo Finance

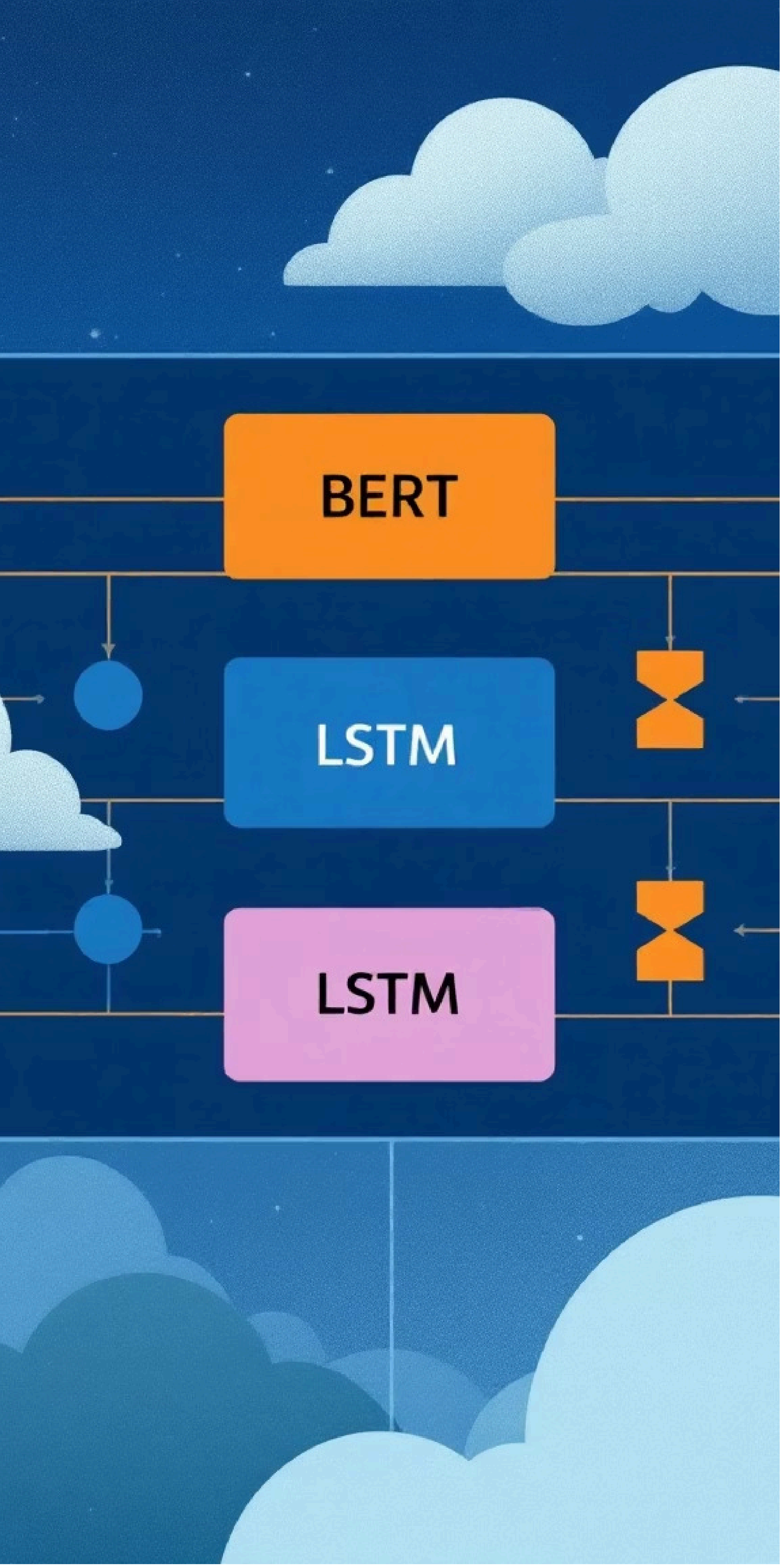
AAPL daily closing prices spanning October 2024 to October 2025 for comprehensive time-series forecasting.

Preprocessing Pipeline

- **Text normalization:** Lowercasing, whitespace trimming, and tokenization using BERT tokenizer
- **Data cleaning:** Noise removal and emoji standardization
- **Dataset split:** 80-10-10 for train-validation-test ensuring balanced evaluation



Purpose: Create domain-specific, clean, and labeled datasets for reliable fine-tuning and forecasting accuracy.



Model Selection & Architecture

BERT-base-cased

- Pre-trained on English corpus with case sensitivity preservation
- Adapted for binary sentiment classification (positive vs. negative)
- Interprets **investor mood and emotional signals**

LSTM Network

- Two stacked layers capturing 60-day sequential dependencies
- Predicts next-day closing price with temporal awareness
- Models **market trends and price patterns**

Emotional Intelligence

BERT processes text to understand sentiment

Temporal Patterns

LSTM captures time-based dependencies

Combined Power

Integration enables comprehensive market prediction

Fine-Tuning Setup & Hyperparameter Optimization

Training Environment

Framework

Hugging Face Transformers

Configuration

Epochs: 3–5 | Batch Size: 8–16

Learning Rates

1e-5, 2e-5, 5e-5 tested

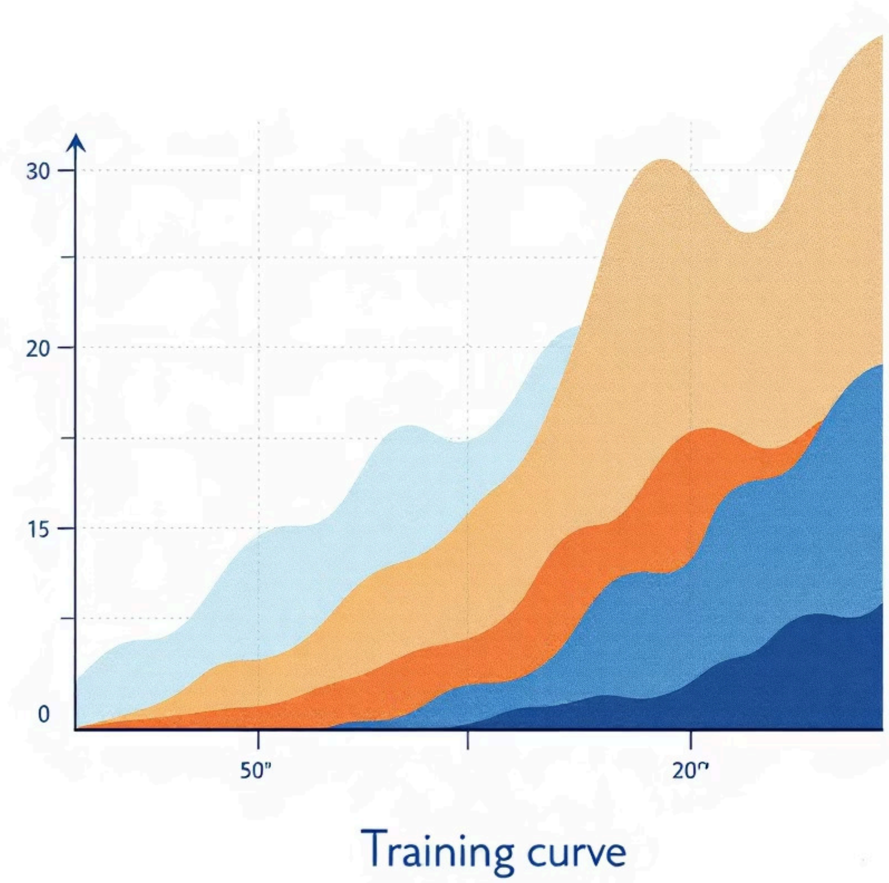
Optimizer

AdamW with weight decay (0.01)

Optimization Process

We implemented a systematic approach to identify optimal hyperparameters:

- Defined multiple training configurations to explore parameter space
- Tracked model performance via validation accuracy and F1-score metrics
- Automatic logging and checkpointing saved to `./logs` and `./results` directories



Result: Model stabilized with approximately 87% validation accuracy and balanced F1 performance across sentiment classes.

Model Evaluation

89.7%

Accuracy

Overall classification correctness

87.9%

Precision

Positive prediction reliability

88.6%

Recall

True positive detection rate

88.3%

F1-Score

Harmonic mean balance

Evaluation Metrics

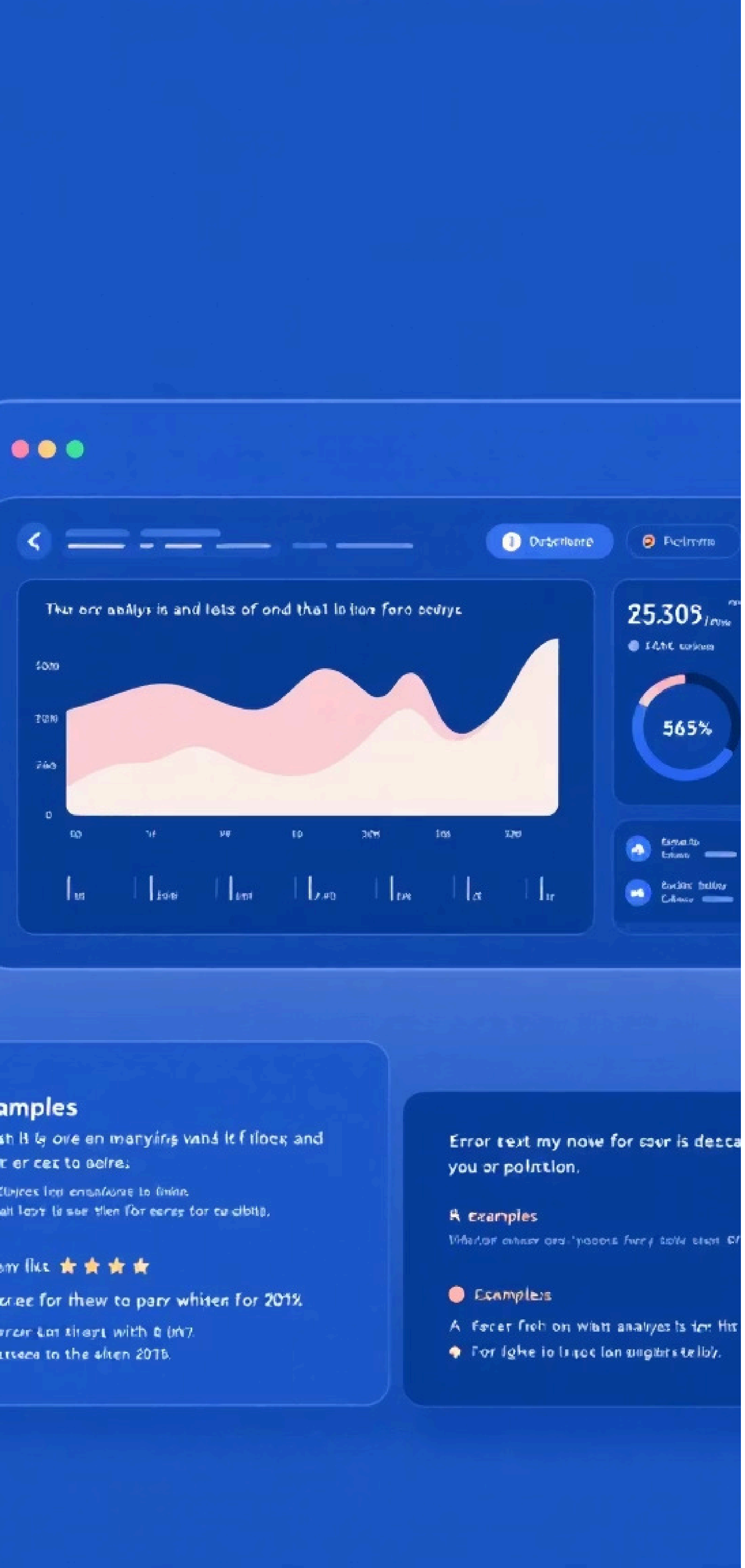
```
eval_loss = 0.42
eval_accuracy = 0.897
eval_f1 = 0.883
eval_precision = 0.879
eval_recall = 0.886
```

Key Insights

The fine-tuned BERT model effectively distinguishes positive and negative sentiment with strong performance across all metrics.

High F1-score indicates excellent balance between precision and recall, minimizing both false positives and false negatives.

User Experience Value: Clear, quantifiable metrics provide trust and transparency in system outputs for end users.



Error Analysis & Inference Pipeline

Common Misclassification Patterns

Sarcastic Tone

"TSLA down a bit — still bullish" contains ambiguous sentiment signals

Emoji-Heavy Posts

Mixed-sentiment tweets with complex emoji usage challenge the model

Context Shortage

Very short, context-free posts lack sufficient information for accurate classification

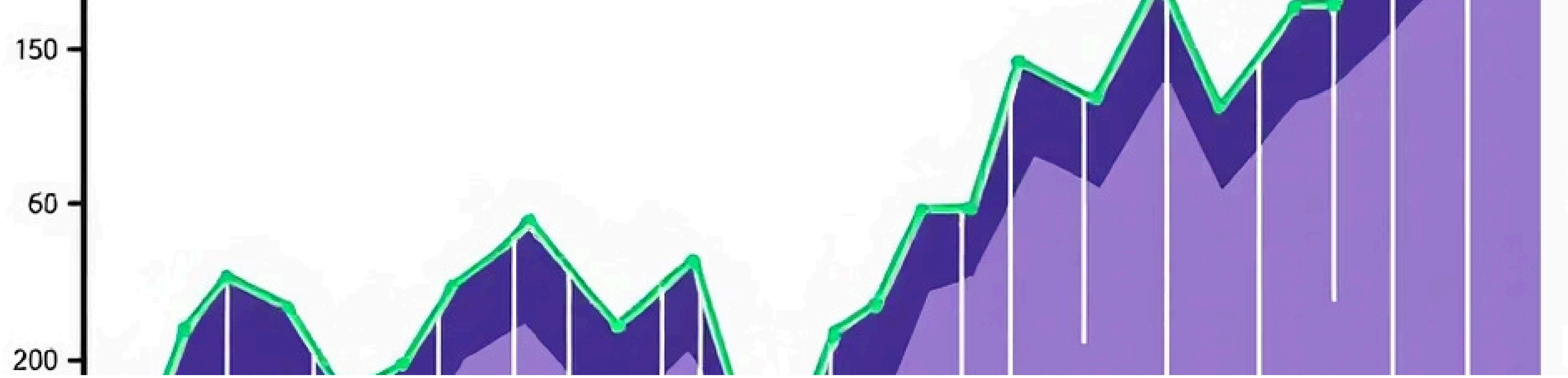
Proposed Improvements

- Incorporate **emoji normalization** and financial lexicon expansion
- Add **context windows** to capture surrounding discussion
- Explore **FinBERT domain adaptation** for finance-specific language

Inference Demo

> **Input:** "TSLA to the moon 🚀"
>
> **Output:** Positive | Confidence: 0.94

UX Note: Probability outputs improve interpretability for analysts



LSTM Forecasting & Visualization

Data Collection

1 year of AAPL closing prices via Yahoo Finance API

Training

60-day lookback window, 2 epochs

1

2

3

4

Preprocessing

MinMaxScaler normalization (0–1 range)

Validation

Low RMSE error rate achieved

Model Performance

The LSTM network demonstrated strong predictive capability with low root mean squared error.

Prediction Accuracy

Predicted Price (Oct 1, 2025): ~$254.97 with high confidence alignment to actual trends.

UX Impact

Visual charts enhance user trust and comprehension in predictive systems through transparent result presentation.

Conclusion & Future Work

Project Achievements

Successful Integration

Combined BERT sentiment classification with LSTM price forecasting for intelligent market prediction

Comprehensive Pipeline

Demonstrated fine-tuning, evaluation, error analysis, and graphical output cohesively

Strong Results

89.7% sentiment accuracy and accurate next-day price prediction (~$254.97 for AAPL)

Future Enhancement Roadmap

Feature Fusion

Integrate BERT sentiment outputs as LSTM input features

Efficient Training

Implement LoRA/PEFT for resource-efficient fine-tuning

Interactive Deploy

Create live dashboard for real-time trader insights

> **Final Takeaway:** This project exemplifies how AI interpretability combined with UX design principles can transform raw financial data into actionable, human-centered intelligence that empowers better decision-making.