



STOCK MARKET PREDICTION USING NEURAL NETWORKS

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OBJECTIVES



Develop a deep-learning model to predict the direction of stock market price movements



Extract useful features from diverse sources of information



Identify correlations between features



Train a prediction model based on extracted features



Make predictions using the trained model to guide investment decisions

DATASETS

- Unrestricted stock market data from UCI Machine Learning Repository
- Daily closing prices of S&P 500, NASDAQ, Dow Jones, NYSE, and RUSSELL 2000
- 82 features: technical indicators, economic data, world indices, currency exchange rates, commodities, and futures contracts
- Data split: 60% training, 20% validation, 20% testing

CURRENT STATE-OF-THE-ART

Advanced neural networks like LSTM for time-series pattern recognition

Blending various models

Enhancing data features

Sentiment analysis using NLP

Transfer learning for refined predictions

Model transparency

Real-time data analysis

Ethical and regulatory compliance

APPROACH

Data preprocessing: handle missing values, normalize features, format for CNN

Exploratory Data Analysis (EDA): trends, correlations, patterns

Model design and architecture selection: 2D CNN for temporal and cross-sectional dependencies

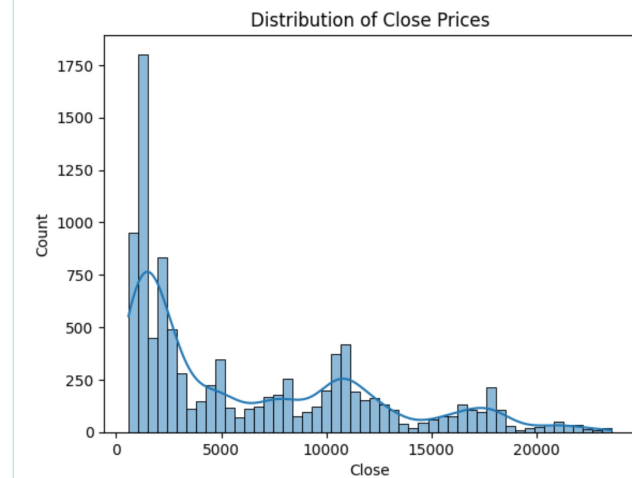
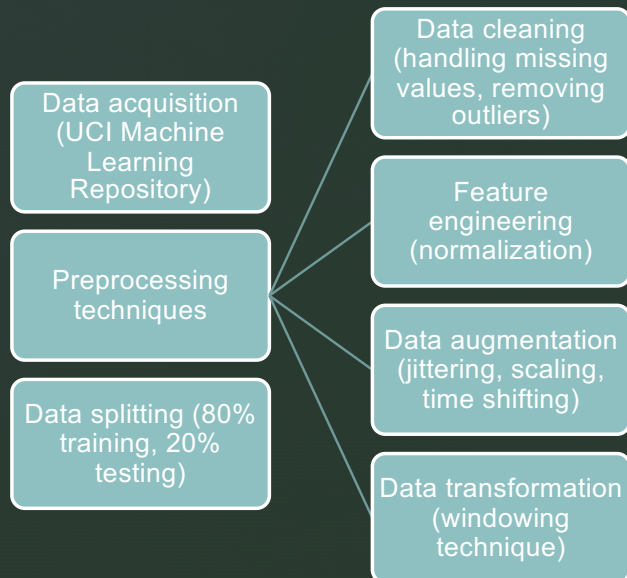
Model implementation and training: TensorFlow/PyTorch, hyper-parameter tuning, regularization

Model evaluation and testing: accuracy, precision, recall, F1-score

Refinement and optimization: architecture adjustments, ensemble learning

Potential enhancement: 3D CNN for capturing multi-dimensional interactions

DATA PREPARATION AND PREPROCESSING



MODEL ARCHITECTURE AND TRAINING

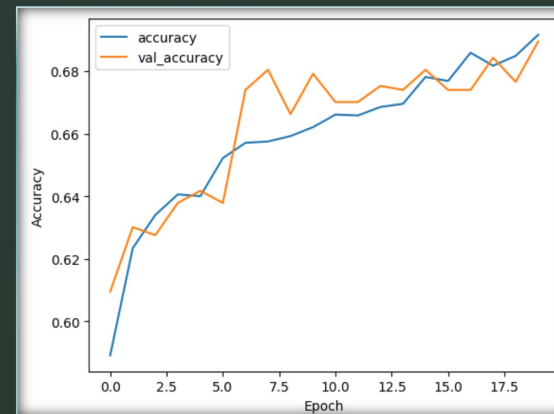
- Initial CNN model and shift to LSTM
- Architecture details
 - LSTM layers (64 units, 32 units)
 - Dropout layers
 - Dense layer (64 neurons, ReLU activation)
 - Output layer (sigmoid activation)
- Optimization and loss function (Adam, binary cross-entropy)
- Model evaluation (accuracy, validation)

Model: "sequential_41"

Layer (type)	Output Shape	Param #
=====		
lstm_26 (LSTM)	(None, 8, 64)	19200
dropout_55 (Dropout)	(None, 8, 64)	0
lstm_27 (LSTM)	(None, 32)	12416
dropout_56 (Dropout)	(None, 32)	0
dense_80 (Dense)	(None, 64)	2112
dropout_57 (Dropout)	(None, 64)	0
dense_81 (Dense)	(None, 1)	65

RESULTS

Training performance
(accuracy graph)



Test performance

- Accuracy: 67.44%
- Classification report
(precision, recall, F1-score)

	precision	recall	f1-score	support
0	0.67	0.70	0.69	970
1	0.69	0.65	0.67	971
accuracy			0.68	1941
macro avg	0.68	0.68	0.68	1941
weighted avg	0.68	0.68	0.68	1941

Comparison with
previous CNN-based
models

CONCLUSION AND FUTURE WORK



Promising results with LSTM model



Potential advantages over CNN-based models



Limitations and considerations



Future explorations
(additional data sources,
feature engineering,
model architectures)



ANY QUESTIONS?

THANK-YOU