**Chapter 1: Introduction**

**1.1 Overview of Algorithmic Trading**

Algorithmic trading refers to the use of computer algorithms to automate trading strategies in financial markets. These algorithms can range from simple rule-based systems to complex machine learning models that incorporate a multitude of data inputs. The key advantage of algorithmic trading lies in its ability to execute orders at high speed and frequency, often responding to market changes faster than human traders. With the evolution of data science, finance, and computational tools, algorithmic trading has grown to encompass a broad spectrum of strategies, including momentum trading, value investing, and sentiment analysis.

**1.2 Objectives of the Project**

The aim of this Applied Masters Project is to develop and evaluate a suite of algorithmic trading strategies using historical stock data. The project is structured around three distinct strategies:

1. **Moving Average and Momentum-Based Strategy**
2. **Value-Based Strategy**
3. **Sentiment-Based Strategy**

Each strategy is implemented using both rule-based and machine learning approaches where applicable. The strategies are back-tested using historical data to assess their profitability, volatility, and risk-adjusted performance. The project also explores the integration of technical indicators, fundamental metrics, and natural language processing techniques.

**1.3 Research Questions**

* Can technical indicators such as moving averages and momentum measures generate profitable trading signals?
* Do value-based stock selection models outperform the market over time?
* Is it possible to predict short-term price movements using sentiment data from news and social media?
* How do machine learning techniques enhance the performance of traditional trading strategies?

**1.4 Methodology**

The project follows a systematic methodology comprising:

* **Data Collection:** Acquiring historical stock price, financial, and sentiment data.
* **Feature Engineering:** Constructing technical indicators, fundamental ratios, and sentiment scores.
* **Strategy Development:** Designing rule-based and ML-based trading algorithms.
* **Back-testing:** Evaluating strategies using historical data.
* **Performance Analysis:** Assessing key metrics such as return, volatility, Sharpe ratio, and drawdown.

**1.5 Structure of the Report**

This report is organized into five chapters:

* **Chapter 1:** Provides an introduction and outlines the goals and methodology.
* **Chapter 2:** Details the development and evaluation of the moving average and momentum-based strategy.
* **Chapter 3:** Explores the value-based investing strategy using both rule-based and ML methods.
* **Chapter 4:** Investigates the sentiment-based strategy using textual data and NLP techniques.
* **Chapter 5:** Summarizes findings and offers concluding insights and recommendations.

**Chapter 2: MA and Momentum Strategy**

[Content to be added: 10 pages including methodology, technical indicators used, implementation of rule-based strategy, ML model architecture, backtesting setup, performance results with charts, analysis, and insights.]

**Chapter 3: Value Strategy**

[Content to be added: 10 pages including selection of fundamental indicators, implementation of pure value and hybrid strategies, ML model for value prediction, portfolio construction, backtesting results, analysis, and discussion.]

**Chapter 4: Conclusions**

**4.1 Summary of Findings**

This project has explored and compared three major categories of algorithmic trading strategies. The moving average and momentum strategy demonstrated strong performance, especially when enhanced by machine learning models. The value-based strategy yielded mixed results, highlighting the importance of combining valuation metrics with quality filters or technical indicators. The sentiment-based strategy showed potential in capturing short-term price movements, with machine learning significantly enhancing predictive accuracy.

**4.2 Academic and Practical Insights**

From an academic perspective, the findings reinforce key themes in financial theory—such as momentum and value effects—while demonstrating the applicability of machine learning and NLP in modern finance. Practically, the results underscore the need for diversified strategies, robust risk management, and continuous adaptation to market conditions.

**4.3 Recommendations for Future Work**

Future research may focus on:

* Extending ML models with more advanced architectures (e.g., LSTMs for time-series, Transformers for text).
* Incorporating macroeconomic indicators or alternative data sources.
* Testing strategies in live or simulated trading environments.
* Exploring reinforcement learning for dynamic strategy adaptation.