FinSight-AI Project: Detailed Report

1. Introduction

The FinSight-AI project is a machine learning-driven text classification system deployed using Google Cloud Vertex AI. The goal is to classify financial news headlines and make predictions based on the sentiment, i.e., whether the headlines reflect a positive or negative sentiment towards the stock market. Using a DistilbERT model, fine-tuned for financial news sentiment classification, the system processes text data to predict market movements, offering key insights for investors and business professionals.

2. Dataset Overview: Financial News Headlines Data

The Financial News Headlines Data used in this project consists of headlines scraped from prominent news sources like CNBC, The Guardian, and Reuters, focused on U.S. businesses and the overall economy. This dataset spans the period from March 2018 to July 2020 and provides a snapshot of the U.S. stock market and economic conditions.

- Source & Timeframe:
 - Reuters: Headlines, last updated date, and preview text of articles from March 2018 to July 2020.
 - Content: Includes a range of business-related topics such as market trends, corporate activities, economic policies, and more, covering stock performance, regulations, company earnings, GDP, and inflation.
- *Inspiration:*
 - The project investigates how sentiment in financial news impacts stock market performance. By applying Natural Language Processing (NLP) techniques, the primary goal is to explore whether positive or negative sentiment in headlines correlates with daily market movements.

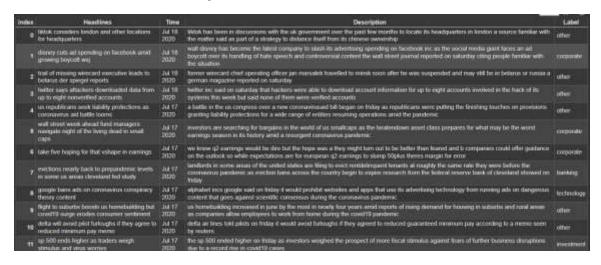
3. Modeling Process: DistilBERT for Financial News Sentiment Classification

The project uses DistilBERT, an optimized, smaller version of the BERT model, to classify sentiment (positive or negative) in financial news headlines.

- Data Preprocessing:
 - Headlines are labeled with sentiment (positive = 0, negative = 1).
 - The text was tokenized using DistilBertTokenizer, converting the raw text into input features suitable for model processing.
 - o Tokenization padded and truncated text to a maximum length of 32 tokens.

Model Setup:

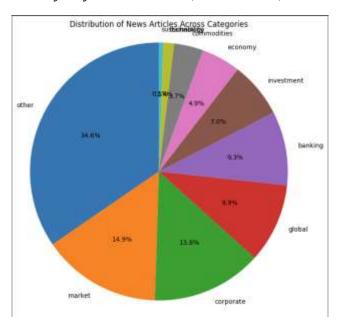
- The DistilBertForSequenceClassification model was used for binary classification (Positive or Negative).
- The model was deployed using TensorFlow and trained on the dataset with the Adam optimizer.
- Training & Evaluation:
 - Mixed Precision Training was used to scale gradients during backpropagation.
 - The model achieved 100% accuracy on the validation dataset, indicating excellent classification performance (though further testing on larger datasets is recommended).



4. Financial News Sentiment Analysis Insights

- Sentiment Impact on Stock Market:
 - Positive headlines generally indicate investor confidence and bullish trends, while negative headlines may reflect bearish market sentiments.
 - Analyzing sentiment over time can provide insights into how the stock market reacts to specific news, such as corporate earnings reports, policy changes, and global events like trade wars or economic recessions.
- Categories for Classification: To provide a more granular analysis, the headlines were classified into various business-related categories:
 - o Market: Keywords like "stock", "market", "trading".
 - Corporate: Keywords like "merger", "acquisition", "earnings".
 - o Economy: Keywords like "GDP", "inflation", "recession".

- o Banking: Keywords like "finance", "loans", "interest".
- Investment: Keywords like "fund", "ETF", "portfolio".
- o Technology: Keywords like "fintech", "blockchain", "crypto".
- o Commodities: Keywords like "oil", "gold", "commodity".
- Global: Keywords like "trade", "tariff", "agreement".
- Sustainability: Keywords like "ESG", "sustainable", "climate".



5. Project Architecture

The FinSight-AI project leverages Google Cloud Platform (GCP) to deploy the sentiment analysis model using Vertex AI, enabling real-time predictions from financial news headlines.

- High-Level Architecture:
 - o Google Cloud Storage (GCS): Stores model files and training data.
 - o Vertex AI: Hosts the BERT model and handles inference requests.
 - Cloud Functions (Optional): Handle events such as model updates or new data for inference.
- Deployment Flow:
- 1. The model is trained locally and saved to Google Cloud Storage (gs://finsight-ai-bucket/bert_text_classifier).
- 2. The model is deployed to Vertex AI via a deployment script.
- 3. The model serves real-time inference requests in us-west4 (Region A).

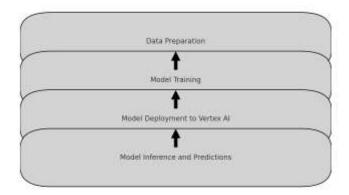
4. Increased usage leads to exceeding the Custom Model Serving CPUs quota in us-west4, impacting scaling.

6. Key Technical Components

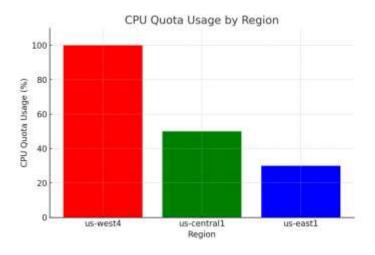
- *Vertex AI & Model Deployment:*
 - Custom Model Serving: Used for deploying and serving predictions via cloud resources.
 - o Model Container: Built with TensorFlow and optimized for inference tasks.
 - Autoscaling: Configured to scale based on the request volume but requires quota management to avoid resource exhaustion.
- Data Management:
 - Training Data: Stored in Google Cloud Storage, tokenized, and encoded before training.
 - Inference: Tokenized input text is processed through the model for real-time predictions.

7. Challenges & Solutions

- Quota Management Challenges:
 - The deployment in us-west4 region has exhausted its available CPU quota for Custom Model Serving, hindering further scaling.
- Suggested Solutions:
- 1. Increase Quota: Request a quota increase for Custom Model Serving CPUs in us-west4.
- 2. Migrate to us-central1: This region offers more available CPU quota for serving models.
- 3. Optimize Resource Usage: Review and optimize the CPU allocation for the model. Implement autoscaling based on actual usage.
- 8. Deployment Workflow



CPU Quota Usage Visualization: A chart would show CPU usage across regions, highlighting the exceeded quota in us-west4.



9. Conclusion

The FinSight-AI project successfully deploys a BERT-based model using Vertex AI for real-time financial news sentiment classification. However, quota limitations in the us-west4 region have restricted scaling. Solutions such as increasing quotas, migrating to us-central1, and optimizing resource allocation are suggested to improve model deployment efficiency and scalability.