Integrating Time Series Forecasting, NLP, and Financial Analysis for Optimal Investment Strategy: A Case Study on Adani Ports

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Abstract*—In the current highly competitive corporate landscape, the utilization of financial forecasting and analysis tools provides a company with a competitive edge, enhancing its decision-making capabilities and overall performance. So this study plans to provide methods that can help startups and failing firms in planning their finances by using ML and AI approaches with limited financial data and resources. To assess the effectiveness of the proposed methodology, an example is taken which is Adani Ports & SEZ, a segment within the Adani Group. By utilizing the past 20 years of financial data and performing NLP on news headlines, important insights and suggestions about opportunities and deficiencies in the near future is provided. Limited historical data availability is a common challenge faced by startups and struggling companies but, we have worked around this problem and have come up with methodologies that is found to be effective. Sentiment analysis using a finetuned FinBERT model is employed to extract valuable insights from news headlines targeting the company which is then combined with its financial records and a multivariate time series forecasting technique employing LSTM is used to forecast potential trends. By integrating financial data with NLP analysis, a holistic understanding of the external factors impacting company performance is achieved. Through the examination of the company's extensive financial data, an effective methodology is developed that can be applied to organizations within and beyond, with similar limitations providing them with valuable financial advice and for maximum benefits.

Keywords—Business Forecasting, Long Short-Term Memory, Multivariate Time-Series Forecasting, Natural Language Processing, News Headlines.

I. INTRODUCTION

Startups usually encounter significant obstacles, and if good planning and resource allocation are not put into practice, they have a high failure rate. Statistics show that a major portion of startups fail within the first few years. According to a CB Insights survey, 42% of firms fail because there isn't a market for their good or service [1]. This tells us how important it is to carry out in-depth market research and understand customer expectations before starting up a business. Startup failure is also a result of lesser resource allocation and improper financial planning. Another statistic by CB Insights, about 29% of failed businesses attribute a significant portion of their failure to cash flow [1]. A startup's growth might be stifled by insufficient funding, bad cash flow management, and inefficient resource allocation.

Commercial decision-making has traditionally made extensive use of conventional business forecasting tools including econometric models and statistical techniques. These tactics usually call for a large outlay of cash and expertise, though, in order to be successful [2]. For startups and smaller businesses, it might be expensive to hire professional analysts or buy expensive forecasting software. These firms may not be able to employ forecasting insights for strategic decision-making since the complexity of these approaches may exceed their skill set and resource capacity. Standard forecasting approaches may thus be inaccessible and unusable for start-ups and firms with low financial resources.

The tests conducted using traditional machine learning algorithms, which are reported in this study, were used to assess and predict the financial records of a company. It analyses deep learning models and autoregressive algorithms before forecasting and conducts an in-depth analysis that includes sentiment analysis of business-related news headlines. Research on business forecasting now has more opportunities thanks to the growth of artificial intelligence [3]. Forecasting models may become more accurate and useful with the use of multilayered perceptron, recurrent neural networks, long short term memory architecture, and other neural network models. Due to the amount of data and increasing computing power, a wider range of businesses, including startups and institutions with little resources, can now use AI-based forecasting.

To better classify financial news and articles, there is still much potential for research in the field of NLP. While conventional NLP techniques can categorize general emotions, it is important to hone and perfect these models, especially for financial situations [4]. This makes it possible to draw important conclusions from vast amounts of financial textual data, enabling more accurate sentiment analysis, event detection, and subject modeling specific to the financial sector. By training NLP models on financial datasets and utilizing domain-specific knowledge, the categorization accuracy and relevance of financial news and texts can be increased. Some examples representing the difference between sentiments predicted by traditional BERT model and finetuned FinBERT for sentiment classification of financial news headlines are shown in Table I.

The finetuned FinBERT model used in this study was trained on a dataset of 11,932 news headlines with sentiments tagged to them. This dataset was obtained from the Hugging Face [25] open-source website (Table II). The model was then used to predict the sentiments of news headlines related to Adani from March 2003 to March 2022 (Table III). There were around 3,800 news headlines related to Adani in this period. The sentiments of these headlines were then used to analyze the trends in Adani's financial statements.

It is necessary to note that factors such as news pertaining to a company or tweets on social media, explain the reasons for fluctuations in the finances of a company. Recent

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company struggles or successes are likely getting a lot of attention online and in the media. This buzz will also be reflected in the company's financial reports. Sentiment analysis can then be utilized to obtain insights of the company's performance. A corporation may be experiencing difficulties if, for instance, its press headlines are starting to become more negative. The corporation might then utilize this knowledge to guide better decisions about its long-term strategy.

TABLE I. TRADITIONAL VS FINANCIAL SENTIMENT

News Headlines	Traditional Sentiment	Financial Sentiment
P&O Ports picks up Adani stake for $60m	Neutral	Positive
Adani Export Q1 net dips 35 pc	Neutral	Negative
Adani plans international airport	Neutral	Positive
Adani loses Gujarat gas city gas distribution network	Negative	Negative

TABLE II. NEWS DATASET FROM HUGGING FACE

News Headlines	News Sentiment
GM loses bull	0
Italy announces guarantee bank loan worth 400 billion euro	1
CSX upgraded buy hold deutsche bank	2

The sentiment 0 refers to negative, 1 refers to positive, and 2 refers to neutral.

TABLE III. NEWS HEADLINES OF ADANI GROUP.

Date	News Headlines
14/10/2003	Adani mulls institute of port management
14/10/2003	Adani to enter education sector
27/08/2004	Adani's get govt nod to develop new sez

Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN), has received a lot of attention in the field of time series forecasting. It was created to overcome the issues that traditional RNNs have with long-term dependency due to the vanishing gradient problem [5]. Due to their memory cells' ability to preserve data over long periods of time, LSTMs are particularly well suited for time series data. In time series forecasting, LSTM models are used to make predictions about future data points based on historical trends. Stacking LSTM layers provide better results than single layered vanilla LSTM [6].The input data, which is a collection of data points, contains seasonality, patterns, and trends that an LSTM model can detect. The LSTM architecture enables it to effectively handle irregular time intervals, missing data, and varied frequencies.

The advantages of LSTMs over traditional autoregressive methods are numerous [7]. A key advantage is their ability to spot and remember long-term dependencies in time series data. Autoregressive techniques, such as ARIMA (Auto-Regressive Integrated Moving Average), can only take into account a certain amount of lagged data points, making it impossible to effectively simulate complex temporal correlations. Additionally, LSTMs can learn from and adapt to non-linear relationships in the data, which is crucial for time series forecasting because real-world data usually contains complex patterns that linear models find difficult to describe [7]. The gates of the LSTM architecture allow it to control the information flow, ensuring that crucial information is maintained and unnecessary noise is filtered out to provide more accurate predictions. Another advantage of using LSTM in forecasting time series is that it can handle multivariate data which results in massive increase in reliability of the forecast.

The study is centered around developing a methodology for forecasting financials and provide the organization with a valuable strategy. This is achieved by forecasting its financial records by utilizing an external factor: News Sentiments of the company. It excludes other economic indicators or even social media comments. The original goal was to work using tweets instead of new headlines, but obtaining tweets connected to the company has been difficult due to Twitter's restricted data scraping policy since July 2023. Hence, exploring news headlines seemed to be a better alternative to the problem. The specific situation at hand raises the following research questions with a thorough evaluation of the literature within the scope of this study: Are deep neural networks better than traditional statistical models in forecasting the financials of a company? Is there a need for special attention when analyzing news headlines for sentiment analysis? Can LSTMs outperform traditional statistical forecasting models when working with smaller financial data? What steps should the targeted company take after analyzing the forecasted data?

These research questions necessitate the design and development of a methodology that any business or organization may use to achieve successful financial planning.

II. RELATED WORK

This session provides a summary of existing literature which relates to the topic of this research.

Janek Ratnatunga discusses the challenges and restrictions of business forecasting [8]. Despite the fact that forecasting can help management accountants create effective plans for future trends and occurrences, the author believes that it is not a perfect process and is frequently more speculative than predictive. They also says that using big data, artificial intelligence, and forecasting technologies prediction accuracy of company's financial data can be improved. In light of unforeseeable events like the COVID-19 epidemic, the study discusses the challenges of forecasting and how it can be more reliable when integrated with other analytical methods.

Isak Hassbring's research [9], is a quantitative case study that investigates the possibility of automating financial forecasting at Ericsson through the use of machine learning. Working with revenue, operational income, and cash flow as the three main financial data sets and projecting them are all part of the study. Machine learning algorithms, such DNNs and random forests, are used to enhance the forecasting process; their effectiveness is compared to more traditional statistical methods. Moreover, machine learning (ML) can improve financial forecasting accuracy, particularly for revenue and operating income. It says that feature selection and data quality has to be monitored carefully for producing accurate outcomes which can be applicable in the commercial sector. The finding is that while ML algorithms are good but, the best outcomes will be obtained when it is combined with established techniques and human knowledge.

A study by Ziliang Shang [10] discusses the evolution of financial analysis and the variables that may impact business value. Starts with common valuation techniques and addresses possible issues with them, such as historical data restrictions and the challenge of piercing corporate walls to conduct a comprehensive study from the viewpoint of the entire value chain and industry chain. A few potential fixes are then offered to address these issues, including employing a mix of quantitative and qualitative techniques and including non-financial aspects in the research. Finally, there is clarity on the significance and application of financial analysis in business forecasting and analysis.

Ibukun Afolabi et al. [11] primarily focuses on constructing a system that can predict success of a business with more than 50% accuracy. It starts by gathering data, analysis, and developing models and evaluating them. The C4.5 algorithm was utilized for decision tree classification. The system provides business owners with insights into their business outcomes for better decision-making and future planning. Future work includes enhancing real-time explanations, incorporating text analytics, and improving accuracy by increasing the data that is used for training.

A study by Francesco Ferrati et al. [13], explores entrepreneurial research by using Crunchbase, a popular platform developed to track startups and venture capital activity. The writers examine Crunchbase's data structure and content, contrast it with other databases frequently used in entrepreneurship studies, and go over certain drawbacks and biases to be mindful of while utilizing Crunchbase data. Following a thorough study of Crunchbase data, it is said that it is a valuable resource for entrepreneurial research but, we must exercise caution when interpreting the data and drawing conclusions as the data contains very less information related to each business and can sometimes be misleading.

The paper by K. Żbikowski and P. Antosiuk [12], explores the use of Crunchbase data to create a bias-free predictive model for forecasting a company's success. They employ a target variable that incorporates data on the IPO, acquisition, and following fundraising rounds, and they restrict the collection of predictors to knowledge at the start of the company's activities. The model presented tends to out-perform other models which were given out as attempts to forecast business performance and offered information that could be useful to founders, investors, and decision-makers. The authors come to the conclusion that firms can predict their success in the actual world by using the suggested strategy.

N. Darapaneni's research study [14] aims to predict the future movement of stocks in the Indian market using historical prices and sentiment data. The researchers used two models, LSTM and Random Forest, to predict the prices of four companies - Reliance, HDFC Bank, TCS, and SBI and concluded that random forest performed slightly better than LSTM in forecasting stock prices. Because stock prices are heavily influenced by public mood, the researchers have conducted sentiment research and have used deep learning approaches for predicting stock values in the Indian market which help traders and investors make wise judgments and is a significant contribution to stock price forecasting. The research faced limitations due to time constraints, technical challenges, and data quality issues which gives rise to future work of manual annotation of data for better quality and fine-tuning the utilized models in this study for better performance.

A research by Y. Pei et al. [15] focuses on stock sentiment analysis using the TweetFinSent dataset. 2,113 tweets spanning over an year with English content filtering was obtained for this study. The annotation process involved three steps: guideline discussion, pilot annotation exercise, and final annotation. The inter-annotator agreement was high, with an overall agreement of 88.5% after conflict resolution. The author experiments various sentiment analysis models on the dataset in-order to showcase the difficulty in capturing news related sentiments from text. Ultimately, the study's "TweetFinSent dataset" provides a wealth of new research possibilities.

S. Taj et al. [16], examines the application of sentiment analysis in the news publishing industry, where there is an explosion of news related data due to the advancements in the IT (information technology) industry. The authors proposes a method of approach for sentiment analysis of news which selects tokens/words/phrases from the news article and the frequencies of each of these are calculated. The identified words are given sentiment scores using the WordNet dictionary. The methodology was used on the BBC news dataset, and the validity of the approach was then assessed. The conclusion drawn from this method is that it can precisely tag news data with an appropriate sentiment.

The research by D. Araci [19] introduces FinBERT, a finetuned language model created exclusively for financial NLP applications and financial sentiment analysis. Using two financial sentiment datasets, the authors evaluate their model by comparing its performance with other pre-trained language models such as ELMo and ULMFit and it turned that FinBERT surpassed most models trained for the same goal and achieved very high performance. The authors conduct experiments to further investigate pre-training on financial corpus, training techniques to reduce catastrophic forgetting, and fine-tuning only a small number of model layers to reduce training time without significantly degrading performance, and conclude that FinBERT is a model with high accuracy for financial sentiment analysis that outperforms other models trained for similar requirements.

III. Implementation Details

To achieve the goals of this study, a methodology is designed that involves experimenting and evaluating various forecasting models, such as SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables), LSTM (Long Short-Term Memory), MLP Regressor (Multi-Layer Perceptron Regressor) and RNN (Recurrent Neural Network), on the available dataset.

The next phase of the research involves retraining FinBERT, an NLP model for sentiment classification of financial news. Since the study aims to tag news headlines with their sentiments, it is essential to pay special attention to the texts' shorter length compared to news articles. In the final step, the best forecasting model is chosen, along with the news sentiments obtained after running the finetuned FinBERT model on the news data corpus, to forecast the company's financials for the next five years. A subset of financial data is used which when forecasted provides us with a better understanding of the company's future and a promising strategy can be developed to overcome any foreseen difficulties or setbacks. The subset of financial data chosen for this study is discussed in Table IV. The definitions of the financial terms are taken from the reference [20].

TABLE IV. FINANCIAL ACCOUNTING TERMS.

Financial Accounting Term	Definition
Operating Income	Profits earned by a business from its regular operations before taxes are subtracted.
Employee Cost	A type of administrative cost associated with benefits provided to employees, including compensation, incentives, post-employment perks, and termination benefits.
Profit/Loss	The difference between revenue and expenses; the amount that remains after deducting all costs from revenue, such as taxes, interest, and depreciation.
Total Current Liabilities	Liabilities that are anticipated to be paid off quickly—usually within a year or less.
Interest	Interest expense typically results from a corporation taking out a capital lease or borrowing money.
Other Expenses	Consists of startup and training costs, general overhead and administrative costs, advertising and marketing, relocation and reorganization costs, redundancy and other termination charges, and other costs.
Depreciation	The methodical distribution of the expenses associated with durable assets, also known as tangible assets, across the anticipated time periods in which they yield financial gains
Other Income	Captures income earned by a company outside of its main business activities
Current Assets	Assets classified as "Current" are ones that are anticipated to be used up or turned into cash very soon—usually within a year or less.
Investing Activities	Investing activities involve the buying and selling of long-term assets and investments.
Financing Activities	Any activity pertaining to acquiring or repaying capital for use in the firm is considered financing.
Cash And Cash Equivalents	Cash (on hand & in bank) + Short-term investments (mature in 90 days) = Cash & Cash Equivalents
Operating activities	Operations that are a component of a company's regular commercial operations, such selling goods and rendering services.
Inventories	The unsold units of product on hand.
Quick Ratio	Cash plus short-term marketable investments plus receivables divided by current liabilities.

A. Predictions

Now, let's elaborate on the models used:

1) SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables): is a well-known time series forecasting model that enhances SARIMA's capabilities. SARIMAX becomes an even more adaptable tool for predicting financial data by including exogenous variables alongside seasonal patterns and autoregressive and moving average components. SARIMAX and other statistical models fall short when it comes to capturing complex nonlinear patterns and artificial neural network models address this issue. This can be concluded by both from references [7] and from this study (Table V).

2) MLP Regressor (Multi-Layer Perceptron Regressor): The MLP Regressor is a form of artificial neural network that models complex data interactions using several hidden layers. Internally, the data passes through non-linear functions making the overall model non-linear [21].

The model has 4 hidden layers all equipped with $ReLU$ function functions. The number of features i.e, input to the model is either 9 or 10 (including news sentiments) hence its mentioned as "n"(Fig 1). First hidden layer has 35, second 70, third 70, and fourth has 40 perceptrons. Finally, the output from the fourth hidden layer is passed through an output layer consisting of a single perceptron which makes the model give a single value output after training on multiple features.

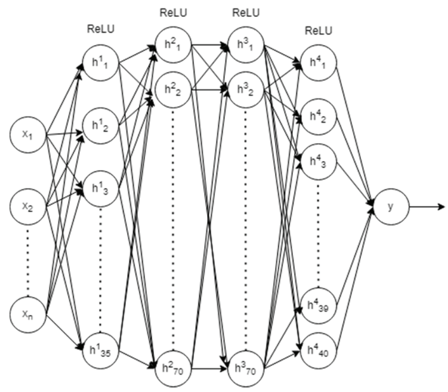

Fig 1: Architecture of the model used(MLP Regressor).

3) RNN (Recurrent Neural Network): RNN is a sort of neural network that uses feedback loops to process sequential data, allowing the network to retain information over time [21]. This makes RNNs most qualified for time series forecasting applications. Traditional RNNs, on the other hand, suffer from vanishing gradient issues [5], which can be addressed by utilizing LSTM.

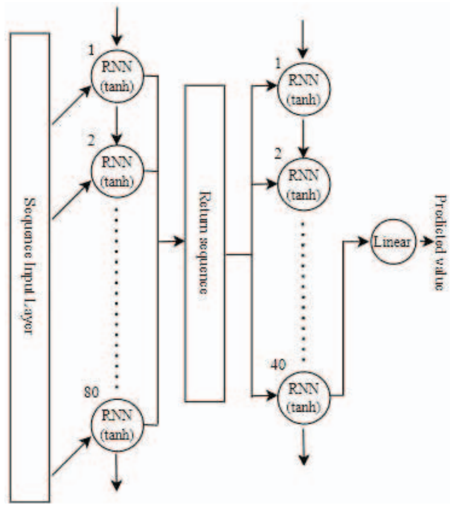

Fig 2: Architecture of the model used(RNN).

RNN architecture used in this case (Fig 2) has two RNN layers both equipped with $tanh$ activation function. The first RNN layer (80 RNN units) returns a sequence which is passed as input to the second RNN layer (40 RNN units). The output of this layer is then passed on to a dense layer which gives a single value output.

4)LSTM (Long Short-Term Memory): LSTM, a more advanced variant of RNN, developed to solve the vanishing gradient problem. To control information flow, it uses memory cells to retain and forget inputs which enables the model to express long-term dependencies in timeseries data. LSTM has been demonstrated to be extremely good in capturing intricate patterns in financial time series [6], making it an excellent tool in this research's forecasting process.

LSTM model used in this study turned out to be the best out of the rest of the models. Detailed data flow is explained in the later sections. The model (Fig 3) consists three stacked LSTM layers with 128 units in the first, 64 units in the second and 32 units in the third layer, each equipped with *tanh* activation function. This is a "n" input 1 output model hence the output of this model is a single value.

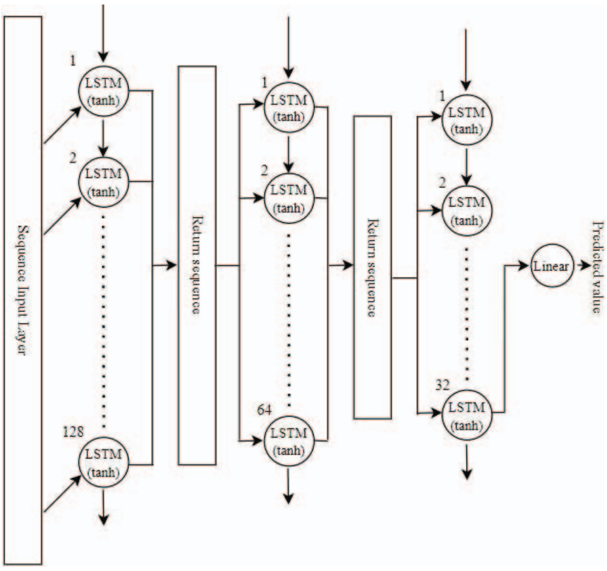

Fig 3: Architecture of the model used(LSTM).

All the hyperparameters used in the above mentioned models are finetuned to give out the best results for the dataset and the Table V reflects the same. Forecast Bias and RMSE (Root Mean Square Error) are calculated using the following formulas [23]:

$$\text{Forecast Bias} = \frac{1}{n}\sum_{i=1}^{n}(\text{Actual Value}_i - \text{Forecast Value}_i) \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{Actual Value}_i - \text{Forecast Value}_i)^2} \quad (2)$$

TABLE V. RMSE VALUES OF VARIOUS MODELS USED.

	SARIMAX	MLP Regressor	RNN	LSTM
RMSE	521.3041	81.9929	38.5032	28.8998
Forecast Bias	640.7208	79.1500	-35.3647	21.6831

It is significant to note that these numbers are rather high due to the little amount of data available.

B. Sentiment Analysis

Conventional NLP models may not effectively classify financial news due to the unique language and context of the domain [4]. To tackle this issue, a unique model is developed by finetuning existing models which focus on analyzing financial news. Words like "fall" and "low" typically indicate negative sentiments in financial contexts, while terms like "gain" and "raised" tend to have positive connotations (Fig 4.).

(a) Most frequent negative terms (b) Most frequent positive terms

Fig 4. Shows most frequent words using in the financing world

Initially, an LSTM model was designed and trained, achieving an accuracy of 51.30%. In the attempt to increase the accuracy, BERT model was finetuned which resulted in a notable improvement, raising the accuracy to 61.38%. To explore more effective models, two specialized pretrained models, RoBERTa and FinBERT, designed for Twitter stock and financial texts, were discovered. Fine-tuning RoBERTa on the dataset led to further enhancement in accuracy, reaching 66.57%. However, the most remarkable results were obtained with FinBERT, which exhibited an astonishing accuracy of 81.90%. This remarkable performance by FinBERT's shows that it is very effective in capturing sentiments of financial texts. The accuracy scores of all models are concisely summarized in the Table VI.

TABLE VI. VALIDATION ACCURACY OF MODELS TRAINED.

	LSTM	BERT	RoBERTa	FinBERT
Validation Accuracy	51.30%	61.38%	66.57%	81.90%

LSTM model designed for the text classification begins by tokenizing and processing text data, establishing a word-to-index mapping, and padding sequences. The LSTM architecture comprises an embedding layer with 90 dimensions, followed by three LSTM layers with 246 units in each, and a 3-unit output layer for multiclass classification. The sparse categorical cross-entropy loss and stochastic gradient descent (SGD) optimizer are used to build the model. Training takes place over 30 epochs with an 8-batch size.

BERT was finetuned for classifying news headlines with the custom dataset (Table II) that was mentioned previously. It uses the BERT-base-uncased model, which consists of twelve layered transformer blocks, each of which has 768 concealed levels and twelve head self-attention layers [26]. It starts by initializing the hidden layer weights of BERT sentiment classification model and the main focus is on tuning the output layer weights. BERT tokenizer is used for tokenizing. [24] says that "lower pre-trained layers learn more general features while higher layers closer to the output specialize more to the pre-training tasks". For a 3k dataset, the model is trained for 7 epochs. Training for three epochs yields good model performance for a downsampled 1k dataset, while additional training for more epochs demonstrates improved model stability [25].

The finetuning of RoBERTa involves similar principles. RoBERTa also uses 12 layered transformer same as BERT, but it has its own tokenizer which uses byte-level BPE [26]. The primary target is to capture sentiments for smaller texts. The model uses a label mapping of {0:negative, 1:neutral, 2:positive} and positions embeddings are of type absolute.

The FinBERT model was fine-tuned for sentiment classification of financial news headlines which are shorter than full news articles. The dataset, presented in Table III, comprises financial news related to the company at focus, sourced from online media websites. It encompasses 3800 news headlines along with their corresponding publication dates. The retrained FinBERT model was then employed to analyze each news headline.

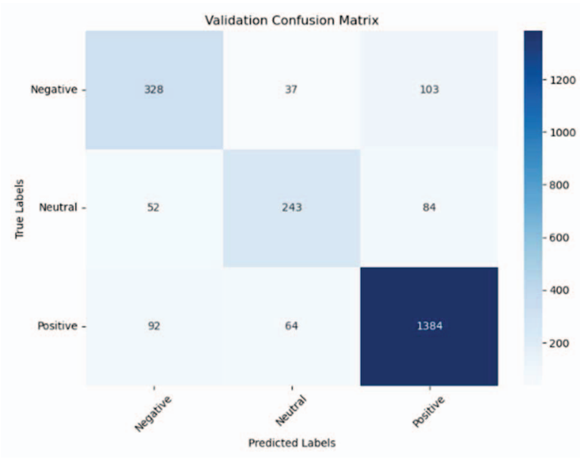

Fig 5. Shows Confusion matrix involving predicted sentiments and true sentiments by fine-tuned FinBERT.

FinBERT is built for classification financial texts [27]. But the model runs on larger texts and our requirement is for financial news headlines which are shorter than usual financial texts. Hence finetuning of this finetuned model is needed in order for it to capture the key essence with lesser number of words in a sentence. Finetuning of FinBERT is done by retraining the model with initial weights same as FinBERT's but, on a dataset mentioned in Table II and involves the same hyperparameters as mentioned earlier for previous models. The learning rate while training is 2e-6 employed with *ADAM* optimizer. [25] presents a case where the authors use a learning rate of 2e -5 and *ADAM* optimizer and conclude that *ADAM* optimizer adaptively re-scales learning rate which is crucial for fine-tuning BERT based models for smaller datasets(< 10K data). The model was trained for 8 epochs with 16 batch size and while tokenizing texts, the max length of tokens was 256 with truncation and adding special tokens. To improve model robustness, a dropout rate of 0.1 was introduced.

TABLE VII. VALIDATION METRICS OF FINE-TUNED FINBERT.

F1-Score	Recall	Precision	Accuracy
0.817585	0.81901	0.81677	0.81901

C. Forecasting

The figure (Fig 6.) shows the steps defined by this study to forecast financials. Now that the model for forecasting and sentiment analysis is chosen, a step by step approach has to be taken in order to achieve the goals of this research. All the steps that were followed are discussed:

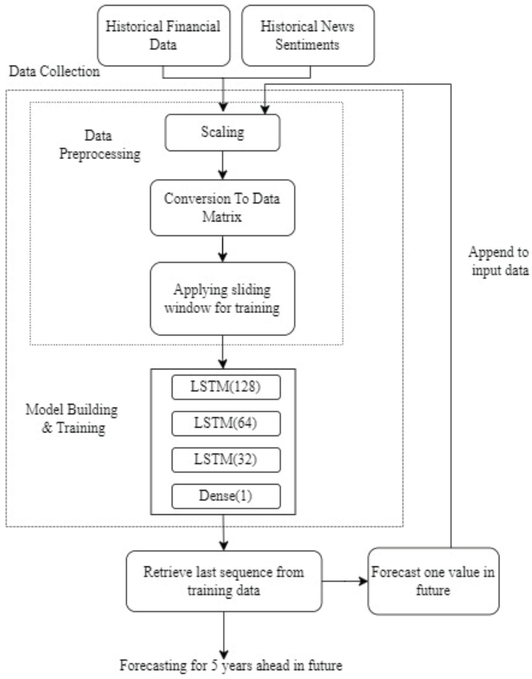

Fig 6. Data flow block diagram for multivariate time-series forecasting.

Data Preparation: The primary step is to obtain the news sentiments. Since the sentiments of news headlines are used to forecast the financials, the selected finetuned FinBERT model is used to predict the sentiments of news pertaining to the company at focus. Once this is accomplished, the data obtained is added to the financial dataset of the company for further processing. This dataset becomes our input data for rest of the processes. Scaling (in this case standardization) the input becomes crucial for LSTMs and other neural network models as they are sensitive to the size of input characteristics [28]. It prevents some features from dominating learning because of their bigger magnitude by ensuring that all features have comparable ranges. Through faster and more consistent convergence during model training, as well as through assisting the neural network in identifying important patterns in the data, this scaling enhances performance and produces more precise predictions.

Model Creation: The LSTM model discussed in section III is built. It consists of 3 layers with the same settings as defined previously. Training this model follows a sliding window technique, where the dataset is traversed by a window of historical data points (14 time steps in this case). The data point immediately after the window serves as the target variable, while the data point inside the window is used as input. Using the input-output pairs created by this process, the LSTM model learns to forecast future values based on previous patterns within the defined timeframe. When used for time series forecasting tasks, the LSTM model then has the ability to detect temporal relationships and produce predictions based on the sequence of prior observations.

Model Training and Forecasting: The LSTM model is then trained on the prepared training data using the historical input sequences and target values. The training is carried out for 10 epochs with a batch size of 16, and a 10% validation split to keep check of the model's performance during training. After training, the last sequence from the input data frame is used to predict the future value using the LSTM model.

The second step in forecasting is making predictions for each column in the original dataset one year in advance and recording the findings in a dictionary. Make each column in the dataset the target variable for forecasting by iteratively going over each one, then receive the target column's predicted value for the following year. This produces one forecast for every attribute in the data frame and is appended to the existing data. This step is repeated iteratively in order to obtain forecast for the next 5 years.

IV. Results and Discussions

The graphs that were plotted show that the frequency of Adani-related news have progressively climbed over time. However, when using the sentiment classification model on Adani news, a significant peak in negative news headlines was observed during 2022-2023, primarily due to the Hindenburg incident (shown in fig 7). Even a minor influx of negative news has substantial repercussions in the business world.

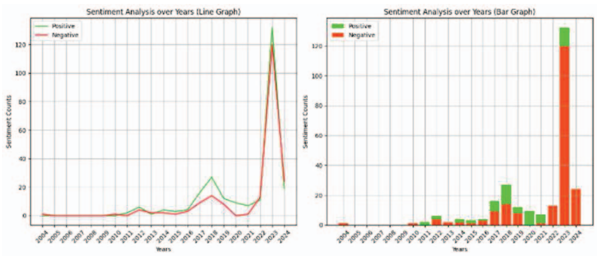

Fig 7. Graphs showing number of positive and negative news headlines over the years related to Adani Group. This classification is done using the FinBERT model trained previously.

Upon comparing the negative news sentiment forecasts with the company's financial statement, a noticeable dip in income, an increase in expenses and, a decrease in profits (resulting in losses) can be observed (Fig 8.). We can assume that the news sentiments are explaining these changes. The income earned by the company other than its main activities(other income) which was a significant amount until 2021 is predicted to drop for the upcoming years. The income from regular operations show a downward trend for the forecasted period.

However, for the year 2024, current liabilities show a significant spike which seems to have been taken care in the next two years. Despite facing obstacles in the recent years, the financials show a good increase in the cash and cash equivalents of the company. This cash could then be utilized to clear its short-term obligations which is reflected by the current liabilities in the year 2025. The company was proactively spending on its investing activities which showed a good increase in assets for the years. Predictions say that, the company will be spending more on its investing activities to obtain assets or to clear its liabilities for the near future. Quick ratio, also known as acid-test is calculated as,

$$\text{Quick Ratio} = \frac{\text{Total Current Assets} - \text{Inventory}}{\text{Total Current Liabilities}} \tag{3}$$

reads 2.3 in the year 2025 and 1.3 in 2026 indicating that the company possesses ample liquid assets to readily settle its short-term debts, bolstering confidence in its financial stability.

Fig 8. Graphs representing financial data. The first set of graphs are plotted from 2007 to 2027 with quarterly data. The values after March 2023 are forecasted by the model defined earlier and are plotted in red. The second set of graphs represent financial data from 2004 to 2028 where the values from 2022 onwards are forecasted values and are plotted in red.

Based on the analysis, cash reserves are increasing, potentially used to cover short-term debt (in 2025). Investment in assets suggest future growth and debt resolution. High quick ratio in 2025 indicates good short-term debt coverage. The possible strategy that can developed on this analysis is that the company should focus more on its core business to improve income and profitability. It has to utilize its cash reserve to pay down debts and evaluate if continued investment spending aligns with the improved financial health. Monitor its inventory to avoid stockouts (negative by 2026). Consider cost-cutting measures to address potential future losses (negative net profit by June 2025).

V. Conclusion

The study starts by exploring various timeseries forecasting models for small datasets. The LSTM architecture along with the proposed methodology showed an exceptional performance for the given scenario. Comparing results from Table V., LSTM model proves to be the best performing model for small timeseries data.

Furthermore, this research produced an improved version of FinBERT that performed better in sentiment analysis of financial news headlines than BERT and RoBERTa.

In conclusion, in-depth analysis of results led to building a sophisticated plan which can then be adopted by the company for a better future. This research considered Adani Ports & SEZ for demonstrating the proposed methodology which can be extended to any other company or organization. Since the LSTM model worked very well on a smaller set of data, the approach is well suited for Startups and failing firms which have unexpected ups and downs in their financials.

VI. Future Work

This study introduces a whole new approach to forecast financials of a company by combining artificial intelligence and financial planning. To take this study further, explore models like transformers for timeseries forecasting can be done. The use of large language model (LLM) to obtain financial news sentiments can be one of the future scopes of this research. Improvements and finetuning the methods can make it as a chatbot or an assistant for financial analysts or business decision makers and help them make sound decisions and experience long-term growth.

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