A Hybrid Deep Reinforcement Learning Framework for Stock Market Prediction

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***Abstract*—Predicting and trading stock values is an intriguing and intricate area of study that keeps getting more and more attention. Generating quick and accurate decisions is essential for generating money in the stock market. Advanced predictive algorithms, made possible by technological advancements, are changing the way investors approach their work. A key component of this shift is the increasing use of automated decision-making processes driven by historical data analysis, especially in the context of individual stocks. Researchers have recently focused on deep reinforcement learning algorithms, which have shown encouraging results and could lead to better stock market forecasts. This paper presents a groundbreaking method that differs from the current models that are based on ANN and LSTM algorithms. Precisely for stock market anticipation, this research constructs a revolutionary architecture by merging ANN, LSTM, and NLP approaches with the deep-Q-network(DQN). This cutting-edge architecture relies on a plethora of stock market data, particularly that pertaining to gold stocks. Extensive dataset validation of the generated model's predictive prowess demonstrates its capacity to estimate the initial stock rate for the upcoming day. In the end, this research adds new dimensions to the field of stock market prediction and provides significant insights.**

Keywords—DRL, machine learning, stock forecasting, neural networks

I. INTRODUCTION

Due to its central role in every economy, stock market prediction has long presented a formidable challenge to statisticians, economists, and other financial specialists. Stocks can be bought, sold, transmitted, and scattered on the market. Initial Public Offerings (IPOs) provide a means for businesses to grow and acquire capital through the stock market [1]. If they are skilled at predicting when to buy and sell specific stocks, investors can profit from their investments in equities of different companies. Due to the dynamic nature of stock values, which fluctuate in response to changes in the market volume of purchased and sold shares, the stock market is notoriously unpredictable. Social media and financial news, for example, can have a beneficial or detrimental impact on stock values, depending on their relevance to national policies, regional and global economy, and psychological and human aspects [2]. The first, known as "fundamental analysis," relies on studying the company's yearly growth rates, dividend payouts, market spot, new deals, income, and expenditures. The second, known as "technical analysis," relies on studying price data and using charts to identify trends and make predictions. Dow Theory is the foundation of technical analysis. Computer scientists, economists, statisticians, and operations researchers are just a few of the disciplines that have taken an interest in stock price prediction.

Research on the topic of stock prediction is presently at a high level of activity. Data scientists began building stock prediction models using algorithms for machine learning. In the past, researchers have used machine learning algorithms to forecast stock market movements based on historical, socialmedia, or news data. It is not always possible to use basic trading tactics to anticipate how different stock markets throughout the world will respond during times of calamity and other dogmatic and monetarist events. The goal of this research is to create a smart system that can forecast stock market trends using the opinions expressed in financial news items as input. New investors will be able to mitigate some of the risk, while seasoned traders will gain some more insight into the market's movement thanks to this study.

An essential part of doing business on a worldwide scale, stock market investment is both a rich and complicated industry that has grown at an unparalleled rate [3]. Recent years have seen the rise of predictive models that use state-of-the-art technology such as ML-strategies algorithms, sentiment analysis, and AI to aid investors in making decisions. LSTM, CCNs, and RNNs are three of the most important methods in this category. Traders and investors can improve their trading techniques with the help of these clever software systems [6]. The complex external factors that impact the market make it difficult for current predictive models to quickly adjust to unexpected market developments. Stock prices are affected by these factors, which might cause unexpected results. Therefore, it is critical to do a basic analysis that takes into account economic aspects and can interpret financial news and occurrences. Achieving precise forecasts from historical datasets—the backbone of stock models—requires painstaking processing due to the presence of noisy data. Accurate forecasting is necessary due to the unpredictable and fast-moving character of financial markets [4].

By using emotion mining from the NLP with deep reinforcement learning (DRL), this research creates a strong cognitive decision-making system, which is a first. Quick market shifts, missing data, and other outside influences are just a few of the challenges that DRL overcomes automatically by processing multi- and high-dimensional resource information and producing actionable outputs based on inputs.

Notable contributions include:

- The use of natural language processing to preprocess media and news data and determine stock market sentiment. To attain the highest level of precision, TF-IDF is used in conjunction with fine-tuning BERT.
- Collecting stock price datasets from authoritative sources like S&P, Yahoo!, NASDAQ, and others.

- The process begins with signal decomposition using variation mode decomposition (VMD), and then LSTM is used to forecast prices.
- Using DRL to forecast stock market values for individual companies based on agents' and actions' behavior by combining natural language processing (NLP), historical data, and SA from news channels.

This document is structured as follows for the sections that follow. Section 2 includes a thorough literature analysis on the subject, while Section 3 dives into the components of the suggested architecture for stock prediction. In Section 4, we cover the implementation and the findings. The study is concluded in Section 5.

II. Literature Review

Models that use technical analysis to identify market patterns from past stock price data typically view prediction as a classification problem; models that use this information to forecast actual stock rate are known as prognostic regression in monetary fiction. Overfitting is an issue when using the simplistic and ignorant methods to real-world problems, and they can't understand long-term trends [5].

Sentiment studies have grown in significance due to the abundance of publicly available textual data, including millions of news stories, social media posts, product reviews, and movie reviews. Data mining and machine learning are crucial for extracting human opinions from large amounts of textual data, which can be used in a variety of contexts. As a result, significant effort is devoted to studying user opinions across domains through sentiment analysis [6]. Rules, lexicons, and machine learning classification algorithms are the basis for the sentiment analysis that can label tweets as good, negative, or neutral according to the sentiment towards the study's field. Comparing Bag-of-Words(BoW) with N-Gram to Part-Of-Speech linguistic annotations, the former performed better [7]. Tweets were determined to be brief and to include organized, non-uniform opinions that fall into positive, negative, and neutral categories when analyzed with NB [8]. The stock market is completely unaffected by tweets and articles on movie reviews; so, when addressing a particular issue, one should utilize the selected tweets that are impacting the relevant study. Using Twitter's movie review data, researchers compared the performance of classifiers. Term Frequency (TF) and TF Inverse Document Frequency (TF-IDF) are neural networks with weighting schemes that were applied to tweets about tech stocks like Facebook, Google, etc. The results showed that the classifiers' accuracy did not differ much, but that TF-IDF performed better than TF [9]. Because it reports on occurrences that directly affect the stock market, the news has an effect on the stock market.

Stock price prediction algorithms that use technical analysis as their guiding concept view market pattern learning from past time series data as a classification problem [10]. Researchers used a variety of machine learning algorithms to forecast stock prices in the past [11] before data from social media and financial news were publicly available, together with algorithms to assess textual data. Since models like ANN and SVM still lack a memory factor, they can't remember the long-term trend and can't predict the stock market's erratic fluctuations. In order to understand the stock market trend, researchers employed a LSTM model based on a RNN. This model outperformed previous versions by learning long-term patterns and predicting the opening price [12]. Outperforming other DL-strategies and any individual design was the hybrid model that combined Empirical Wavelet Transform (EWT) with LSTM and PSO. Maximum long-term profit maximization in the face of complicated stock price volatility was the goal of training an ensemble of DQL models [13]. The Chinese stock market used an attention-based bidirectional LSTM that was trained using real-world transaction records, a CNN to derive a daily group trading vector, and a DSPNN to make predictions. The attention strategy and bidirectional structure of DSPNN allowed the model to outperform LSTM.

III. Proposed Methodology

Here we'll break down the entire process that the proposed framework for stock prediction goes through. The stages depicted in Fig. 1 are also part of the proposed framework. In order to forecast the stock price, financial news is sent into MLP Regressor together with historical stock data, which has already been processed by a number of sentiment analysis algorithms to provide sentiment scores (Fig 1). Also covered are the specifics of the process and data collection.

A. Deep Learning

In order to do jobs like classification and regression, ANNs imitate the intricate processes of the human-brain. ANNs are composed of layers of linked neurons. Present ANNs, driven by GPUs and TPUs, support multiple hidden layers, improving their capacity to identify nonlinear patterns. This is in contrast to traditional ANNs, which were restricted to a few layers due to computational checks (Fig. 1). Many domains find uses for deep learning with ANNs, such as computer vision, healthcare, and predictive analytics.

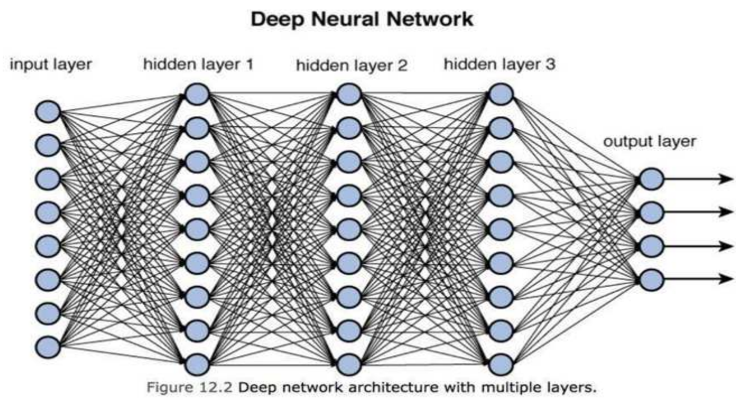

Fig. 1. DNN Architechture

B. Reinforcement learning

An agent's decision-making process in reinforcement learning is extended to many circumstances. Everyone from the agent to their surroundings, deeds, consequences, and findings are part of it [14]. Overly frequent reinforcements and high computing costs are two of reinforcement learning's biggest concerns, particularly when dealing with complicated situations. Fig. 2 captures the dynamics of reinforcement learning by showing the agent's interaction with its surroundings. Importantly, the agent does not know what state they will be in next, even when they do the same action again and again, because in this concept, states are stochastic.

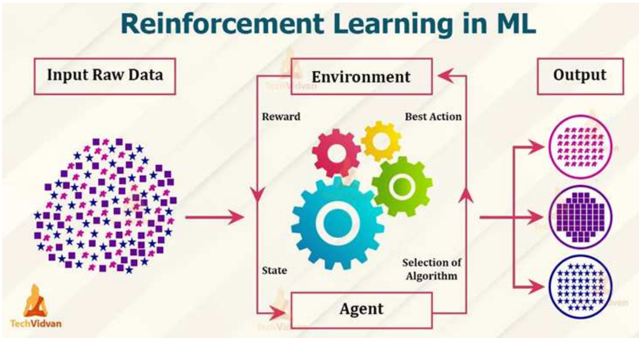

Fig. 2. Work flow diagram of the RL

The key to success in the intricate stock market environment is accurate price forecasting. Investors' confidence is a key factor in determining whether they will purchase, hold, or sell equities in the face of market uncertainties, therefore accuracy is of the utmost importance. A great deal of academic work has stressed the absolute importance of efficiency in solving the problems of stock price prediction. Giving investors the information they need to make smart decisions, accurate forecasts are not just beneficial, but crucial [15]. An essential idea in this field is market efficiency, which describes a situation in which stock prices accurately reflect the information that is currently available in the trading markets. You must understand that these price changes might not be based only on fresh data, but they could be impacted by old data as well, which means the results are naturally hard to forecast. Our research aims to improve the accuracy of stock price projections in this environment, helping investors make educated and confident decisions.

C. A Hybrid approach for stock prediction

In order to forecast stock prices, this study employs the DRL model, natural language processing, and variational mode decomposition with RNN. In order to maximize profit, the model collects stock historic and news data and then decides whether to purchase or sell. In Fig. 3, you can see the design. There are three stages to the architectural development process: natural language processing (NLP), visual machine learning (VMD) with RNN, and DRL.

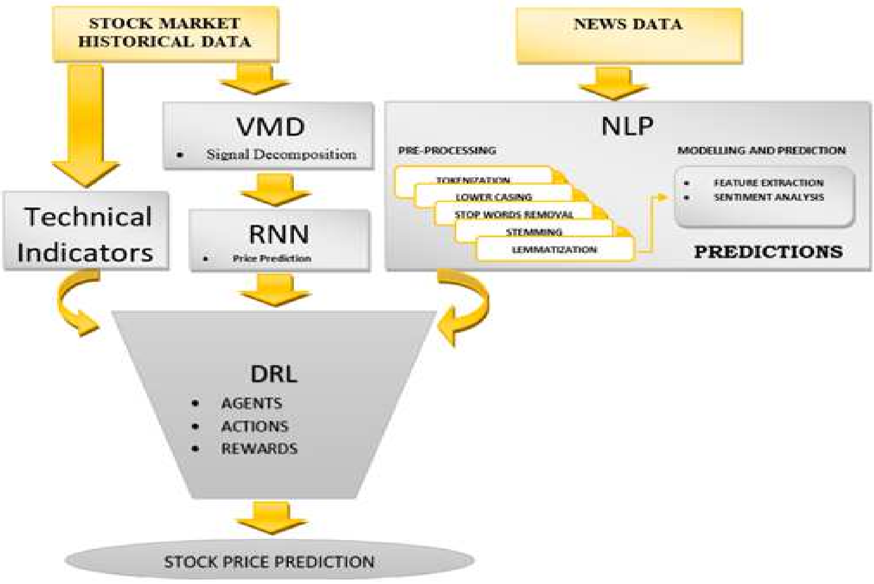

Fig. 3. Proposed Model architecture

So, datasets from the past and current, such as those from media or news, are essential to the suggested algorithm and design. Normal language processing (NLP), prediction, and deep reinforcement learning (DRL) are the three parts that make up the architecture. In order to get stock forecasts, the sentiment and analysis algorithm integrated with DRL.

IV. RESULTS AND DISCUSSIONS

We use cloud GPUs to execute our framework, taking use of cloud computing's benefits for better processing power. At every stage, the code undergoes rigorous evaluation and adjustment to guarantee the highest level of accuracy. A thorough evaluation and comparison with benchmark trading methods confirm the efficacy of the suggested framework.

A. Sentiment Analysis Phase

To find the best algorithm, the sentiment analysis phase tests a number of classification algorithms with varying preprocessing models. Table 1 shows that the data demonstrate that TFIDF and BERT together are better than each one alone, with a combined accuracy of 96.8%. We ran a battery of analytics, including methods for categorization and finding instances of model overfitting. Understanding the training-prediction dynamics was much aided by visualization, particularly when utilizing ANN with BERT and TFIDF. Fig. 4 shows that the ANN model performed exceptionally well, with an accuracy rate of 98.06%.

TABLE I. PERFORMANCE EVALUATION

Model	Accuracy (%)
TFIDF+ANN	86
BERT+ANN	97
BERT+TFIDF+ANN	98.06

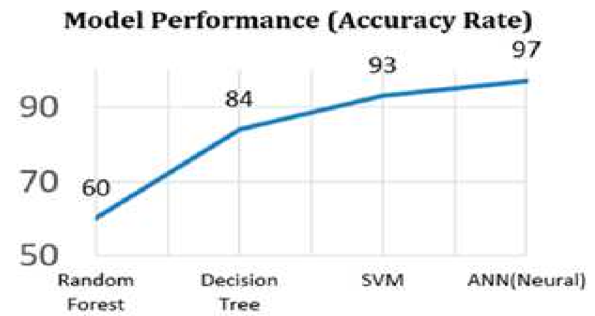

Fig. 4. Performance Analysis

Compared to the other combinations, BERT with TFIDF and ANN produced greater accuracy (Table 1). With these expected results and calculated values, the BERT model proves to be an accurate and unbiased predictor. Sentiment sensitivity, word count, and null statements were the basis for BERT's performance. Although many factors, including sentence length, word count, and contradicting claims, affected the BERT model's performance, its resilience and lack of bias are demonstrated by this.

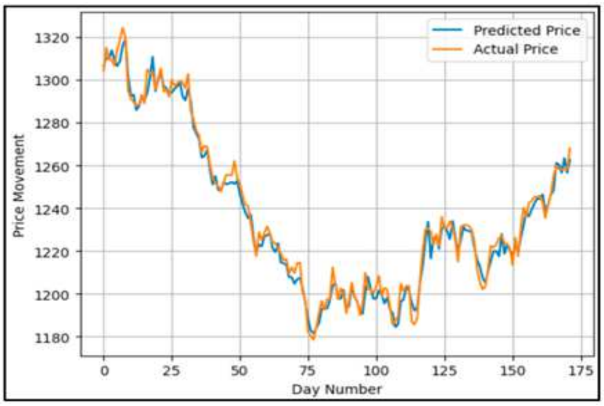

Fig. 5. Actual Vs predicted values

Predictions made in this phase accurately inform decisions made in the DRL phase, so keep that in mind. Fig. 5 displays the outcomes of comparing the real and anticipated prices, which allows us to assess the prediction's efficiency. The chart clearly demonstrates the effectiveness of our prediction module, as the real and forecasted prices exhibit a strong correlation.

The decision-making process will proceed to the DRL phase. The well-known DQL architecture, which is a subset of value-based DRL algorithms, is used for the implementation. Setting up the network that was put into place. Two DNN—the main network and the target network—form the reply buffer upon which the DQN depends. The two networks are identical in design, consisting of three layers.

Deep reinforcement learning (DRL), more especially the value-based method known as the deep Q learning architecture, is used in the last decision phase. Included in the state representation are elements such as past and future prices, results of sentiment research, and technical indicators such as momentum and relative strength index (RSI). Purchase, increase purchase, sell, and further decrease sales make up the action space. If the stock price forecast step is accurate, the entire framework will be efficient. For trading strategies to be effective, the DRL model must be able to make educated decisions based on these forecasts.

Those benchmark trading techniques are contrasted with the outcomes produced by the suggested framework. According to the results, the suggested framework performed better than the other algorithms across all of the criteria. All of the performance metric numbers are from the same gold dataset. We compared the DQN findings to those of the other methods. In order to demonstrate how well the algorithms worked, we generated these graphs. Fig. 6 shows the results of the annualized wealth rate algorithm's metrics graph.

We also do additional experiments in the same setting to demonstrate how effective our suggested approach is when applied with sentiment analysis. After incorporating the sentiment analysis module into our system, we saw a considerable boost in performance, as shown in Fig. 7. Various numbers of episodes are used in the trials. At least ten runs of each episode count are required to get an accurate average. Performance in these trials is evaluated in the following ways. We compare the closing prices of the two days to see how they compare. It is the right thing to do if the algorithm decides to sell as the price goes up. But it's a bad move if the algorithm goes ahead and buys something. Here, performance is measured by the algorithm's accuracy as a proportion of all activities.

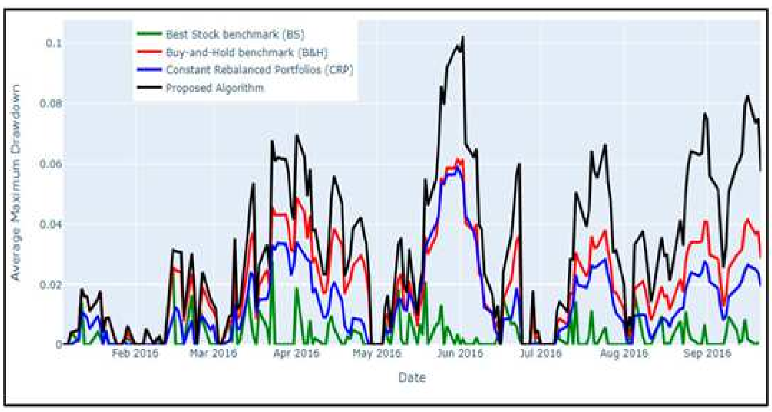

Fig. 6. Comparative Analysis

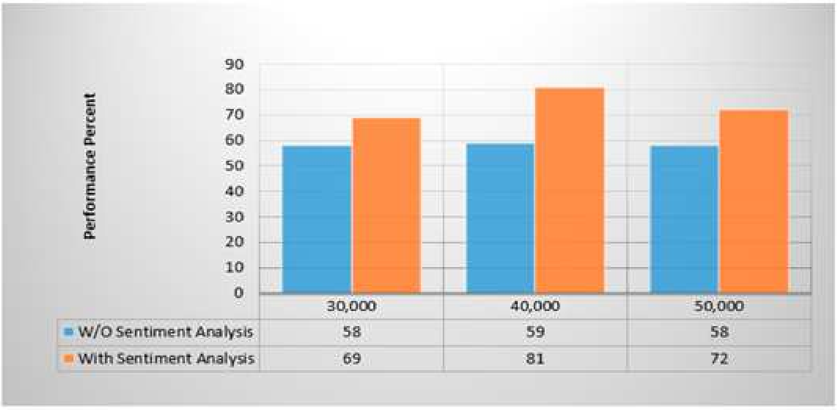

Fig. 7. Outcome of utilizing the SA in proposed model results

V. CONCLUSIONS

This study introduces a revolutionary architecture that integrates many anticipation algorithms to accurately predict stock value. The analysis anticipated gold prices for investors using gold databases. Gold datasets from S&P, Yahoo, and NASDAQ represented stock market data. The predictive framework used NLP to process social media sentiments, LSTM networks to analyze historical data, VMD for feature selection, and ANNs to predict. The research also used DRL and DQNs to merge opinions with other algorithms to anticipate the next day's initial stock price based on past data. The prediction model was built using precisely reported training and testing data methods. Performance measurements showed greater accuracy in the suggested design after intensive study. Graphical representations showed high values at specified times or days, meeting benchmark norms. The comparison showed that the DQN beat previous algorithms, demonstrating the architecture's potential to predict stocks with unmatched accuracy.

Future work into real-time applications in dynamic situations like livestock markets is promising. Such implementations may reveal the model's efficacy and flexibility in varied market circumstances. This study shows that the framework is general, making it suitable for use with items other than gold. This adaptability makes the approach powerful for traders and investors across sectors. Further investigations on real-time livestock market data will prove the framework's efficacy and allow for customized modifications to specific industries and market complexities.

REFERENCES

[1] Kaur, G. and Sharma, A., 2023. A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. Journal of big data, 10(1), p.5.

[2] Das, N., Sadhukhan, B., Ghosh, R. and Chakrabarti, S., 2024. Developing Hybrid Deep Learning Models for Stock Price Prediction Using Enhanced Twitter Sentiment Score and Technical Indicators. Computational Economics, pp.1-40.

[3] Peivandizadeh, A., Hatami, S., Nakhjavani, A., Khoshsima, L., Qazani, M.R.C., Haleem, M. and Alizadehsani, R., 2024. Stock market prediction with transductive long short-term memory and social media sentiment analysis. IEEE Access.

[4] Wilson, A., 2024. Integrating Sentiment Analysis and Machine Learning for Robust Stock Price Prediction: A Comprehensive Study Exploring the Synergy of Sentiment Data and Historical Stock Prices for Accurate and Reliable Market Predictions (Doctoral dissertation, Dublin Business School).

[5] Li, W., Hu, C. and Luo, Y., 2023. A deep learning approach with extensive sentiment analysis for quantitative investment. Electronics, 12(18), p.3960.

[6] Praturi, S.S.G., Ramakrishnan, A. and Deepthi, L.R., 2023, July. Stock Price Prediction Using Sentiment Analysis on Financial News. In International Conference on Data Science and Applications (pp. 551-567). Singapore: Springer Nature Singapore.

[7] Gandhudi, M., Alphonse, P.J.A., Fiore, U. and Gangadharan, G.R., 2024. Explainable hybrid quantum neural networks for analyzing the influence of tweets on stock price prediction. Computers and Electrical Engineering, 118, p.109302.

[8] Kumar, G.R., Latha, S.B., Shaker Reddy, P.C. and Sucharitha, Y., 2024. Multi-agent Iot-based System for Intelligent Vehicle Traffic Management Using Wireless Sensor Networks. Recent Advances in Electrical & Electronic Engineering (Formerly Recent Patents on Electrical & Electronic Engineering), 17(5), pp.515-522.

[9] Shaker Reddy, P.C., Sucharitha, Y. and Vivekanand, A., 2024. Customer Churn Prevention For E-commerce Platforms using Machine Learning-based Business Intelligence. Recent Advances in Electrical & Electronic Engineering (Formerly Recent Patents on Electrical & Electronic Engineering), 17(5), pp.456-465.

[10] Saravanaraj, S.S., Govindan, V., Donganont, M. and Said, B., 2025. Integrating Neutrosophic Logic with Bi-directional LSTM Model for Predicting Stock Market Movements. International Journal of Neutrosophic Science, (2), pp.84-4.

[11] Patel, R., Chauhan, J., Tiwari, N.K., Upaddhyay, V. and Bajpai, A., 2024. A Deep Learning Framework for Hourly Bitcoin Price Prediction Using Bi-LSTM and Sentiment Analysis of Twitter Data. SN Computer Science, 5(6), p.767.

[12] Din, R.U., Ahmed, S. and Khan, S.H., 2024. A Novel Decision Ensemble Framework: Customized Attention-BiLSTM and XGBoost for Speculative Stock Price Forecasting. arXiv preprint arXiv:2401.11621.

[13] Thakur, G.K., Kulkarni, S., Kumar, K.S., Sudarsanam, P., Sreenivasulu, M. and Reddy, P.C.S., 2024, July. An Enhanced Prediction of Ovarian Cancer Based on Ensemble Classifier Using Explainable AI. In 2024 2nd World Conference on Communication & Computing (WCONF) (pp. 1-6). IEEE.

[14] Deng, S., Luo, Q., Zhu, Y., Ning, H., Yu, Y., Gao, Y., Shen, Q. and Shimada, T., 2024. Multi-sentiment fusion for stock price crash risk prediction using an interpretable ensemble learning method. Engineering Applications of Artificial Intelligence, 135, p.108842.

[15] Kulkarni, S., Thakur, G.K., Bhargavi, K., Babu, C.R., Madhavi, G.B. and Reddy, P.C.S., 2024, July. A Hybrid Deep Learning Framework for Gastrointestinal Tract Classification Based on Endoscopic Images. In 2024 2nd World Conference on Communication & Computing (WCONF) (pp. 1-6). IEEE.