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**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

A Project Report

on

**“IPO Forecasting with Temporal Fusion Transformers: A Comparative Study with Deep Learning Models”**

Submitted in fulfillment of the requirements for the award of the Degree of

**BACHELOR OF TECHNOLOGY**

**IN**

**ARTIFICIAL INTELLIGENCE AND DATA SCIENCE**

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**2024 - 2025**

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**DECLARATION**

We, **Rayan Rafi Sheikh (R21EH096), Aditi Sinha (R21EH110), B Mahima (R21EH112) and Bharath J Ramalingam (R21EH113)** students of Bachelor of Technology, belong in to School of Computer Science and Engineering, REVA University, declare that this Project Report entitled **“IPO Forecasting with Temporal Fusion Transformers: A Comparative Study with Deep Learning Models”** is the result the of project done by us under the supervision of **Dr. Shantala Devi Patil, Professor** at School of Computer Science and Engineering, REVA University.

We are submitting this Project Report in partial fulfillment of the requirements for the award of the degree of the Bachelor of Engineering in Computer Science and Engineering by the REVA University, Bangalore during the academic year 2024-2025.

We declare that this project report has been tested for plagiarism and has passed the plagiarism test with the similarity score of less than 20% and it satisfies the academic requirements in respect of Project work prescribed for the said Degree.

We further declare that this project report or any part of it has not been submitted for award of any other Degree / Diploma of this University or any other University/ Institution.

*Signature of the candidates with dates*



*Certified that this project work submitted by* ***Rayan Rafi Sheikh (R21EH096), Aditi Sinha (R21EH110), B Mahima (R21EH112) and Bharath J Ramalingam (R21EH113)*** *has been carried out under my / our guidance and the declaration made by the candidates is true to the best of my knowledge.*

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| *Date: …………….* | *Date: …………….* |

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| *Signature of HoD* | *Signature of Director* |
| *Date: …………….* | *Date: …………….* |
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**SCHOOL OF** **COMPUTER SCIENCE AND ENGINEERING.**

**CERTIFICATE**

Certified that the project work entitled **IPO Forecasting with Temporal Fusion Transformers: A Comparative Study with Deep Learning Models** carried out under my guidance by **Rayan Rafi Sheikh (R21EH096), Aditi Sinha (R21EH110), B Mahima (R21EH112) and Bharath J Ramalingam (R21EH113)** are bonafide students at REVA University during the academic year 2024-2025, are submitting the project report in partial fulfillment for the award of **Bachelor of Technology** in Computer Science and Engineering during the academic year **2024-2025.** The project report has been tested for plagiarism and passed the plagiarism test with a similarity score less than 20%. The project report has been approved as it satisfies the academic requirements in respect of Project work prescribed for the said Degree.

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<List of Group Members>

**Contents**

|  |  |
| --- | --- |
| List of tables with titles and page references | <Page No> |
| List of illustrations / Screen Shots if any, with titles and page references | <Page No> |
| List of Symbols, Abbreviation of Nomenclature | <Page No> |
| Abstract | <Page No> |
| 1. Introduction | <Page No> |
| 1. Literature Survey | <Page No> |
| 1. Positioning | <Page No> |
| * 1. Problem statement | <Page No> |
| * 1. Product position statement | <Page No> |
| 1. Project overview | <Page No> |
| * 1. Objectives | <Page No> |
| * 1. Goals | <Page No> |
| 1. Project Scope | <Page No> |
| 1. Methodology | <Page No> |
| 1. Modules identified | <Page No> |
| 1. Project Implementation | <Page No> |
| * 1. Architectural Design, Circuit Design (Hardware Project) and Mechanical and Control Unit Design (Robotics or automation projects) | <Page No> |
| * 1. Class Diagram | <Page No> |
| * 1. Entity Relationship Model | <Page No> |
| * 1. Sequence Diagram | <Page No> |
| * 1. Description of Technology Used | <Page No> |
| 1. Findings / Results of Analysis | <Page No> |
| 1. Cost of the Project | <Page No> |
| 1. Conclusions | <Page No> |
| 1. Project Limitations and Future Enhancements | <Page No> |
| References | <Page No> |
| Appendices, if any | <Page No> |
| Copies of Articles: | <Page No> |
| Conference papers published (Certificate with Published Paper) | <Page No> |
| Patent Forms | <Page No> |
| Plagiarism Report………………………………………………………………………. | <Page No> |
| Any Awards achieved (Certificates) | <Page No> |

**ABSTRACT**

*Initial Public Offerings (IPOs) are essential for private companies seeking access to public markets and capital. Predicting IPO outcomes, such as pricing and performance, has become increasingly data-driven with advancements in machine learning (ML) and deep learning (DL). ML models like decision trees and random forests excel at analyzing structured financial data, while DL models, including recurrent neural networks (RNNs) and convolutional neural networks (CNNs), identify complex patterns and temporal dependencies. Recent developments in predictive modeling have introduced advanced techniques such as Lasso regression for feature selection, gated recurrent units (GRUs) for improved time-series analysis, and attention mechanisms that enhance model interpretability. These methodologies improve the accuracy of IPO predictions, enabling investors and stakeholders to make more informed decisions. One of the most promising approaches is the use of Temporal Fusion Transformers (TFTs), which integrate multiple data sources and model dependencies across time, significantly refining IPO analysis. By leveraging these powerful tools, financial experts can enhance forecasting accuracy and navigate market uncertainties more effectively. By reviewing methodologies and highlighting challenges, this study demonstrates how we can reshape IPO analysis with the use of TFTs, enabling more accurate data-driven decision-making in financial markets and address the issues that were observed in the previous models. Continuous refinement of ML and DL methodologies and adequate understanding of the financial market, will help in building a more suitable model.*

***Keywords: -***

*IPO prediction, machine learning, deep learning, neural networks, RNN, CNN, financial analysis*

**CHAPTER - 01**

**INTRODUCTION**

Initial Public Offerings (IPOs) serve as a milestone for private companies, and that gives them access to public markets, raise substantial capital, and enhance their market visibility. Accurate prediction of IPO outcomes, such as pricing, first-day returns, and long-term performance, is essential for investors, regulators, and company stakeholders to make informed decisions. Although traditional financial metrics and qualitative evaluations have long been used for IPO analysis, the increasing complexity of market dynamics requires the adoption of advanced data-driven approaches.

Machine learning (ML) and deep learning (DL) models have emerged as powerful tools in financial prediction tasks, leveraging their ability to analyze large datasets and extract meaningful insights. ML models such as decision trees, support vector machines, random forests, and ensemble techniques have been extensively employed for IPO prediction. They excel in handling structured data and identifying influential features such as earnings per share, market conditions, and industry-specific factors.

Deep learning models, including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformer-based architectures, have pushed the boundaries of prediction accuracy. These models can capture non-linear relationships, temporal dependencies, and intricate patterns in financial data. For instance, RNNs are particularly useful in analyzing sequential data like market trends, while CNNs are adept at extracting features from graphical or tabular data representations. In addition, hybrid models that combine the ML and DL methods are gaining traction because of their ability to balance interpretability and predictive performance.

However, existing ML/DL models face limitations in IPO prediction due to their inability to capture long-term dependencies, sensitivity to market volatility, and lack of interpretability. RNNs and GRUs struggle with vanishing gradients, CNNs are not inherently suited for sequential data, and traditional transformers are computationally expensive. Addressing these gaps, this study introduces Temporal Fusion Transformers (TFTs), which combine multi- horizon forecasting capabilities, gated residual networks, and attention mechanisms to improve IPO performance prediction.

Temporal Fusion Transformers (TFTs) offer a powerful solution by incorporating multi-horizon forecasting, selective feature importance weighting, and self-attention mechanisms. Unlike traditional deep learning approaches, TFTs provide uncertainty quantification, making them well-suited for financial prediction tasks like IPO forecasting.

This study proposes a novel TFT-based framework for IPO performance prediction and evaluates its effectiveness against traditional ML/DL approaches. The contributions of this study are as follows:

(1) We introduce the application of Temporal Fusion Trans- formers (TFTs) for IPO performance prediction, demonstrating their effectiveness in capturing multivariate time-series dependencies.

(2) We compare TFTs against traditional ML/DL approaches, highlighting their advantages in predictive accuracy and interpretability.

(3) We provide an in-depth analysis of feature importance in IPO forecasting, offering insights for financial decision- makers.

**CHAPTER – 02**

**LITRATURE SURVEY**

**A. Introduction**

Accurately predicting an Initial Public Offering (IPO) performance is a critical challenge in financial markets. There have been a lot of previously tried and tested methods, which include traditional models, such as GARCH and regression-based approaches, which rely on historical data but struggle with market volatility, investor sentiment, and long-term dependencies. Machine learning (ML) techniques, including Random Forests, Gradient Boosting, and Support Vector Machines (SVMs), have improved prediction accuracy by analyzing complex financial indicators. Deep learning models like RNNs, LSTMs, and CNNs further enhance forecasting by capturing sequential dependencies.

Recent advances integrate sentiment analysis and hybrid models, combining fundamental and market-based indicators. However, these methods still face key limitations, including:

(1) Short-term focus, lacking multi-horizon forecasting capabilities.

(2) Limited interpretability, making it difficult to understand key financial drivers.

(3) Inability to dynamically adapt to changing market conditions.

**B. Traditional Financial Models**

Guzman et al. (2010) [1], explored advancements in predicting IPO pricing and performance using machine learning techniques, focusing on SBIR awards to identify significant variation in startups’ exit orientation.

Meghna et al. (2019) [2], examined IPO Pricing using statistical techniques and a GARCH model to evaluate long term IPO performance in India. Their analysis found no significant impact of dividend policy on IPO prices, but IPO underpricing was evident in short term trends.

Rui Ge et al. (2023) [3] used a Lasso based regression model, demonstrating that Retained profits per Share (REPS) are the most important predictor of IPO pricing in the Chinese market, which achieved a 70% accuracy in IPO Pricing forecast.

These models analyzed structured data, such as financial ratios, company fundamentals, and market conditions in particular. However, they failed to capture non-linear dependencies in IPO Performance and did not adapt to external market shifts such as investor sentiment and macroeconomic trends.

**C. Machine Learning Based Approaches**

Quintana et al. (2017) [4] demonstrated that Random Forest outperformed traditional regression models for IPO prediction, achieving a higher predictive accuracy ( 65.21%) due to its robust ability to handle high-dimensional financial data, and their resilience against outliers, as compared to IBK, multi- layer perceptrons, and radial basis neural networks. They were particularly effective in ranking IPOs based on their potential initial returns and reducing under-pricing errors compared to observed outcomes.

Pravinkumar et al. (2023) [5] compared various ML algorithms, such as AdaBoost, Random Forest, Logistic Regression, Artificial Neural Networks, and Support Vector Ma- chines, coming to the conclusion that Artificial Neural Net- works were the most effective, achieving a 68.11% accuracy and highlighting the importance of specific factors.

These Machine Learning Models improved IPO forecasting by handling structured financial data and ranking important features, which led to improved classification accuracy. This came with a lot more feature engineering required to set up, as well as struggles with accurately taking into account time- series dependencies.

**D. Deep Learning Approaches**

Murugan (2018) [6] explored Recurrent Neural Networks (RNNs) for financial prediction, highlighting their effective- ness in processing sequential data, such as time-series data, spoken language, and sound. Having an intrinsic feedback loop that allows retention of temporal context across sequences led them to be very effective at tasks like language modeling, stock market prediction, etc.

Calafiore et al. (2019) [3] developed a ”Neuro-Survival” model, integrating Neural Networks with a Survival Analysis framework to examine the timing of the IPO within a specified timeframe, to provide accurate estimations of the time-to-IPO probability and successfully forecast the likelihood of IPO occurrences.

Ni (2022) [8] applied CNNs and LSTMs to IPO prospectus analysis, achieving higher accuracy by combining text-based financial data with historical stock trends. LSTM have loops and a hidden state that enable the network to deal with sequences and store historical data in the hidden state. Two sets of weights are used in RNNs: one for the inputs and one for the hidden state vector. The network learns weights for the inputs and the hidden state during training. Both the hidden state, which is dependent on earlier inputs, and the current input are used to determine the output when it is implemented.

The ability of simple RNNs to learn longer-term dependencies is constrained in practice. RNNs are frequently trained via backpropagation, which can cause either an explosive or disappearing gradient issue. In applications where the network must learn long-term links, these issues limit effectiveness by making the network weights either extremely small or extremely high.

Deep Learning Models, particularly LSTMs and CNNs, are effective in capturing nonlinear relationships and sequential dependencies. RNNs have difficulties during training, espe- cially when it comes to controlling gradient flow during back- propagation, which can result in problems like vanishing or inflating gradients. They also lack multi-horizon forecasting, and require large datasets for training.

**E. Sentiment Analysis and NLP**

Ly & Nguyen (2020) [9] examined the predictive power of sentiment analysis applied to IPO prospectuses such as Form S-1, which offer valuable insights into the investment offerings and the company’s prospects. Evaluating their performance across various timeframes showed a 9.6% improvement in classification accuracy over random baseline models.

Emidi & Gala´n (2022) [10] used Topic Modeling and Logistic Regression to analyze IPO prospectus sentiment. Their analysis reveals that variables like IPO price, ”SPAC,” ”commerce - retail,” and ”tech - entertainment” are crucial, while ”insurance - healthcare” and ”digital solutions” reduce accuracy of the model. This led to the conclusion that market sentiment influences IPO pricing and performance more than fundamental metrics alone.

Natural Language Processing models leverage investor sen- timent, textual data, and financial reports to a great extent, improving the IPO predictions to reflext in-market trends more accurately. These NLP models do require extensive pre processing and often lack contextual accuracy without additional financial indicators.

**F. Hybrid Approaches**

Baba & Sevil (2020) [11] found that ensemble models, such as Gradient Boosting and Stacked Neural Networks, improved IPO classification accuracy.

Neghab & Cevik (2023) [12] introduced Explainable AI (XAI) techniques like SHAP values to enhance interpretability in IPO price forecasting. They found that the offer price is the most significant predictor of IPO under-pricing, followed by equity retained and assets. It also reveals that under-pricing tends to be more pronounced in technology-based sectors, and during IPO surges, higher dispersion in firm quality leads to greater under-pricing. Tree-based models, particularly decision trees, outperformed other ML techniques in both regression and classification tasks. These findings underscore the importance of considering industry sector and market conditions when evaluating IPO pricing.

Bastı et al. (2015) [13] analyzed Turkish IPOs and found that market sentiment plays a crucial role in IPO performance, supporting the cyclical behaviour theory, where IPOs in bull markets tend to have higher initial returns. Their approach, combining decision trees (DT) with SVMs provide more reliable insights by combining results from different algorithms through data fusion and sensitivity analysis.

Hybrid models improve feature selection, prediction accu- racy, and explainability in IPO forecasting, however these methods still rely on predefined feature sets, struggle with multi-horizon dependencies, and lack dynamic weighting mechanisms.

**G. Research Gap**

Significant advancements have been made in the field of predicting IPO outcomes, and there still exist gaps that mostly arise due to key limitations such as traditional models’ lack of ability to capture complex relationships, ML and DL models’ struggle with interoperability and long-term dependencies. When targeted with Sentiment Analysis methods, they require external financial context for a more accurate analysis, while Hybrid approaches lack dynamic feature weighting and they fail to provide uncertainty estimates in predictions.