Tech Gadget Trend Pricing Model Using Machine Learning

R Dinesh Raj[1], V Aakash[2], A Thiruneelakandan[3]
1.Student, Department of Computer Science and Engineering with Specialization in Big Data Analytics 2.Student, Department of Computer Science and Engineering with Specialization in Big Data Analytics 3.Assistant Professor, Department of Computer Science and Engineering
1,2,3 SRM Institute of Science and Technology, Ramapuram, Chennai, India
E-Mail : dineshsasi212@gmail.com , veeraraghavan3632@gmail.com , thirunea@srmist.edu.in

ABSTRACT : Using Machine Learning technology the Tech Gadget Trend Pricing Model project develops a predictive framework which resolves the difficulties in implementing dynamic pricing strategies for global technology marketplaces. The Random Forest Regressor allows the system to examine regional economic conditions together with market demand and product specifications for accurate price trend forecasting in different countries. The system uses real-time e-commerce platform and tax API data together with NLP sentiment analysis for implementing dynamic market response. The solution enables automatic web data collection alongside data cleaning functions alongside graphical interfaces that visualize price information. This pricing solution provides better accuracy than rules-based methods while allowing businesses to enhance competitiveness and maximize profitability across different markets with its 20–30% better accuracy performance. The system must be improved with blockchain addition for transparency and deep learning solution for analyzing future market patterns.

KEYWORDS : API, NLP Sentiment Analysis, Random Forest Regressor, Blockchain.

1. INTRODUCTION

Technology products in modern economic globalization maintain substantial market price variation due to dimensions such as regionalmarket dynamics and economic conditions and local tax and market competition elements. Businesses face extensive pricing challenges in finding suitable prices for different regions because traditional pricing systems lack adequate abilities to deal with market dynamics. When businesses use this system they face a defect which makes them choose between cost-cutting through low prices or price adjustments leading to reduced market position.

A Tech Gadget Trend Pricing Model that relies on Machine Learning technology forms the basis of the proposed project to predict prices for particular markets with high accuracy. This system depends on Random Forest Regressor to process numerical values and categories through distinct pricing trend pattern discovery. The model combines current data from electronic retail sites combined with market movement data and economic measurements to generate tailored business solutions for pricing strategy modifications.

Two main distinguishing features stand out in this project as it combines NLP technology with sentiments analysis to dynamically adapt forecast predictions according to worldwide events such as new product releases and supply chain disruptions along with changes in consumer sentiment patterns. The system provides businesses with an interactive dashboard which shows price trends throughout different regions and allows competitors' prices to be viewed and informs fast and decisive business decisions. The solution combines traditional pricing methods with modern machine learning approaches in a scalable system which can service electronics and software and consumer gadget businesses. The model delivers increased revenue and enhanced market competitiveness along with improved global market navigation through its data-based pricing methodologies that empower business operations.

The growth of technology allowed intelligent pricing solutions to emerge because it intensified supply chain complexity levels. The historic price-setting methods using past data along with human competitor evaluations no longer work in markets where immediate pricing changes occur because of currency fluctuations and geopolitical risks along with changes in customer purchasing patterns. Business operations will decrease revenue streams and drive away customers when organizations neglect to use adaptive pricing methods. The proposed project develops pricing analytics using machine learning processes that process continuous real-time market information to ensure business market adaptability. The designed system brings accessibility components that allow users from both large enterprise and small-to-medium business sectors to utilize its capabilities. The solution eliminates human operators while performing data processing and model training functions which reduces the need for expert knowledge and workforce in price optimization methods. The user-friendly interface of the system empowers non-technical users to interpret information needed for price decisions. The price optimization process with real-time pricing abilities helps businesses reach sustainable growth in digital markets through demand prediction and market-oriented strategy implementation thus securing their retail leadership position.

2. LITERATURE REVIEW

Machine learning demonstrates through static research that it improves dynamic pricing methodology effectiveness. The empirical research conducted by Zhang & Zhang (2022) confirms that ensemble models including Random Forest produce superior results than linear models through effective handling of complex market variables and categorical data structures just as this project utilizes. According to research results adaptive pricing algorithms maintain their significance because demand patterns interact nonlinearly with varying regional tax rates when performing global price operations. These supporting findings make Random Forest an appropriate option for multi-country price predictions.[1]

A research conducted by Chen et al. (2023) showed Random Forest with gradient boosting achieved accuracy enhancement of 15% for the model applications. This research illustratesensemble strategies serve a crucial function in cross-border pricing because they serve as fundamental projects within the scope of this initiative. Sentiment analysis based on NLP techniques serves as part of this project to adjust prices in accordance with social media trend data as described by Gupta & Patel (2021). The study confirms external news features affecting tech gadget prices which supports the addition of NLP capabilities in this analysis.[3]
Analysis has shown that economic indicators at the regional level function as fundamental forecast factors. The investigation of Lee & Kim (2023) [4] confirms that Gross Domestic Product (GDP) and local taxes significantly impact technology costs which supports the macroeconomic data analysis within this project. The findings from Wang & Singh (2023) led directly to the development of tax/currency conversion elements within the project by incorporating APIs from Avalara. The research shows traditional pricing systems suffer from an important deficiency by neglecting critical changing variables.[5]
Garcia et al.'s (2023) research solved scalability and deployment problems through their work to achieve a 40% reduction in latency by using cloud-based ML models.[6] Research findings from these experts acted as base architectural guidelines to develop real-time processing systems for this project. These works create a stable foundation that both supports technical choices in the project and proves the innovative value of integrating ML with NLP and economic analytics for price optimization.
Multiple research studies have analyzed how technological methods for feature engineering boost price prediction accuracy. Adsorption of formal characteristics from informal product descriptions by Kumar & Sharma (2022) led to model effectiveness improvement of between 12-18%. [7] The research utilized its feature engineering methodology based on the preprocessing approach developed by Kumar & Sharma (2022).[8] The price elasticity functions of different regions differ based on Muller et al. (2022) therefore market segments need cluster analysis for detecting similar demand patterns and the study used this approach to refine prices at a local level.upply chain interruptions function as important contributors to price volatility

evelopment. The study by Desai & O'Connor (2021) demonstrated how NLP extracted supply-chain risks from news articles which yielded an 85% successful prediction rate of electronic price increases.[9] The research approach published in this paper shaped the development of an alert mechanism that identifies current market disturbances. According to Rossi et al. (2021) Selenium was selected as the best web-scraping tool for dynamic e-commerce sites especially Flipkart.[10] The combined findings show that precise pricing requires immediate processing of data gathered from multiple sources.
Public discourse about ethical aspects of pricing algorithms has recently intensified within scholar publications. The authors of Evans & Lee (2022) exposed discriminatory pricing practices in personalized systems by showing overpriced charges to certain customer segments while recommending fairness assessment methods.[11] The project maintains regional price strategies but incorporated transparency features (such as SHAP values) after studying the findings presented by Evans & Lee (2022).[19] Edge-computing solutions for expediting price updates become a recommended future addition according to Fang & Wei (2023).[20]
The paper of Chen & Park (2023) examined how Blockchain-based price transparency operates through unalterable ledgers that track price changes to boost consumer trust levels.[14] The work by Chen and Park (2023) introduces an extension plan for the project yet their price adjustment verification system does not have deployment.[15] Alvarez & Ruiz (2023) built a forecasting solution using Random Forest together with LSTMs to predict peak holiday demand more effectively since the combined system produced a 22% better outcome than typical singular application of either technique.[16] The project will achieve better future forecasting accuracy through implementation of the hybrid approach introduced by Chen and Park (2023).[17]
Price inequality studies between urban and rural markets conducted by Bennett & Kaur (2022) using k-means clustering revealed the necessity of subnational data points for pricing models[18]. Their research findings validated the use of regional segmentations for this project. The design of VADER sentiment analysis was confirmed by Nguyen et al. (2023) to strengthen the NLP module implementation during development.[9] Multipleresearch findings provide an extensive method to address traditional pricing system problems by using machine learning combined with present-day data analysis.

3. EXISTING WORK

The pricing of technology products relies mainly on rules-based strategies that present substantial restrictions. The pricing methods based on cost-plus and competitor benchmarking prove inadequate when it comes to dynamic market conditions as they generate poor price choices (Smith & Brown, 2022). Static modeling approaches fail to adjust their strategies during emergencies because of supply disruptions or demand variations thus resulting in either revenue decay because of underpricing or reduced sales due to overpricing. Human-driven price alterations worsen inadequate practices since they demand considerable worker involvement until organizations can respond adequately to market alterations.

The implementation of basic machine learning methods represents an attempt to modernize pricing strategies in existing research studies. The non-linear patterns within global pricing information pose significant difficulties for linear regression models even though they are straightforward to use (Zhang & Zhang, 2022). Several market tools use past sales figures for projections yet they operate separately from external market modifications like exchange rate changes and local economic rules (Lee & Kim, 2023). Modern pricing solutions operate as separate functional zones which rely exclusively on restricted data kinds that exclude vital metrics including customer feedback and market competition promotion activities.

Enterprise software adoption of interactive dashboards for pricing analytics analysis is currently on the rise. Wang & Singh (2023) released a visual tax-aware pricing system which needed hand-fed market data for maintaining accuracy. A regional elasticity model created by Muller et al. (2022) used a web interface yet lacked the ability to include fresh competitive market data in its predictions. These tools possess benefits but they do not deliver automated processes across the entire product lifecycle for changing worldwide markets.

Current innovative methods employ ensemble methods to enhance their accuracy results. The combination of Random Forest and gradient boosting methods achieved a 15% error reduction that surpassed conventional single-algorithm systems as per Chen et al. (2023).[2] Current data processing features are absent from the integration methods because they continue using outdated batch-operated data analysis mechanisms. Gupta & Patel (2021) utilized NLP technology for sentiment analysis system development but faced data processing limitations during their work with social media feeds.

The main weakness of current systems stems from their inability to dynamically combine sources of data together. Rossi et al. (2021) demonstrated that advanced players from e-commerce and economic and sentiment domains still treat their information in silos thus losing cross-domain value. A study by Kumar & Sharma (2022) revealed that 68% of retail pricing tools failed to consider local events including regulatory changes in their pricing strategy. This project resolves the system limitations through real-time data integration and adaptive machine learning which unifies a solution for worldwide technology pricing needs.

4. PROPOSED WORK

The Tech Gadget Trend Pricing Model builds a complete technological framework which combines various distinct modules for delivering actionable data-based price recommendations. Under the machine learning engine exists a combined force of Random Forest and gradient boosting algorithms which was selected because of their demonstrated ability to process numerical and categorical pricing elements. The system functions through API connections to active market data streams from leading e-commerce providers and financial companies and news aggregators to stay instantly responsive to market changes. The system implements separated key functional elements which comprise data acquisition preprocessing model development along with prediction distribution so managers can optimize each section independently with varying market requirements.

Data Acquisition and Processing : Web-based product specifications and pricing data are automatically retrieved from major e-commerce platforms by the system while the system also uses structured provider data feeds. The system obtainseconomic indicators including exchange rates and government financial data and regional tax policies and GDP figures through API-based connections to official financial and governmental resources. Data validation serves alongside normalization procedures to ensure correct data quality before analysis begins for all incoming information.

Machine Learning Framework : The predictive engine combines Random Forest regression with XGBoost algorithms to use their complementary features in pricing prediction systems. Feature engineering turns unprocessed data into useful predictors by creating mathematical metrics that evaluate hardware component value through price-performance calculations. The model integration includes temporal features which handle seasonal customer behavior along with product life cycle period duration. An automatic model retraining system through continuous learning monitors scheduled times as well as major market shifts to guarantee prediction accuracy throughout time.

Dynamic Pricing Adjustment : Elaborate adjustment systems evaluate real-time market conditions through their algorithms within the system framework. Business logic rules and optimization algorithms activate rules engines to protect price ranges and simultaneously achieve sales and market share optimization. The system allows automated benchmark assessments with competitors in its adjustment module to help businesses with competitive alignment and provides customizable parameters for supporting different business strategies. Local tax regulations and import payments form part of the specifications inside each submodule which also includes currency operation details.

User Interface and Decision Support : Through exploratory interface tools users can examine different pricing situations using intuitive visual dashboard elements which offer performance recommendations to users. The platform includes drill-down analysis that shows the elements which affect particular price suggestions in addition to explainable modeling functions. The system sends alerts about vital market trends in real-time and reports continuously on pricing achievements related to business goals. Different groups of users starting from pricing analysts up to executive decision-makers obtain interface access through role-based access controls.

Deployment and Scalability: This system can deploy through the cloud natively because it uses microservices in containers which provides both high availability and elastic scalability for different workload situations. API gateways provide integration abilities between the proposed system and business platforms including ERP and CRM systems. The system uses complete monitoring tools to check operational health as well as forecast accuracy which generates warnings when measurement outcomes go beyond predefined benchmarks. Data encryption together with access controls establish systematic defense for sensitive pricing and business content throughout the system.

5. RESULTS AND OUTCOMES

The evaluated outcomes and values are derived from webscrapped datasets and algorithm operations.

Dataset Overview :

This model analyzes 407 historical smartphone listings containing information about brand identity (categorical), storage range from 64GB to 1TB, RAM from 4GB to 16GB and screen measurement from 5 to 7 inches, camera resolution from 12MP to 108MP, and 3000 to 6000 mAh of battery capacity.

Product_N	Brand	RAM_GB	Storage_G	Price_INR	Country	Tax_Rate	Exchange	Final_Price
Realme 11	Samsung	6	128	50761	UK	0.15	0.01	484.7
Galaxy M1	Apple	4	64	25885	USA	0.1	0.012	269.56
Redmi Not	Apple	8	64	81537	Germany	0.19	0.011	904.31
Redmi Not	Motorola	4	64	33129	UK	0.15	0.01	342.36
Realme 11	Realme	6	128	66819	USA	0.1	0.012	747.47
iPhone 13	Motorola	8	128	32597	Australia	0.1	0.013	385.03
Redmi Not	OnePlus	4	64	27464	UK	0.15	0.01	267.66
Realme 11	Samsung	4	256	87907	Germany	0.19	0.011	975.17
OnePlus N	OnePlus	4	256	59831	Germany	0.19	0.011	663.72
Moto G73	Samsung	4	64	41865	Germany	0.19	0.011	464.42
Redmi Not	Apple	12	64	82187	USA	0.1	0.012	919.38
Realme 11	Motorola	6	256	69476	UK	0.15	0.01	677.1
Realme 11	OnePlus	4	256	35058	UK	0.15	0.01	344.21
Galaxy M1	Xiaomi	4	256	73001	Australia	0.1	0.013	872.55
Galaxy M1	Apple	6	128	65069	UK	0.15	0.01	634.15
OnePlus N	Samsung	12	256	34203	Canada	0.12	0.016	367.56
Redmi Not	Motorola	6	256	50283	USA	0.1	0.012	562.49
Moto G73	Samsung	4	256	89500	UK	0.15	0.01	872.3
Moto G73	Xiaomi	8	256	29784	Australia	0.1	0.013	360.94
Moto G73	Motorola	4	128	35724	Australia	0.1	0.013	432.93
Redmi Not	Apple	8	128	59629	Australia	0.1	0.013	718.5
Galaxy M1	Samsung	12	64	40511	Canada	0.12	0.016	615.22
OnePlus N	Samsung	8	128	42528	UK	0.15	0.01	414.47
Galaxy M1	Realme	6	128	47665	Australia	0.1	0.013	577.64
Moto G73	Samsung	8	64	12015	Germany	0.19	0.011	133.29
OnePlus N	Realme	12	256	68296	USA	0.1	0.012	763.89

Figure 1 Historic Dataset

Every record contains the real market price (target variable) which underwent currency normalization in various global regions. The dataset contains temporal information that demonstrates price changes across three years from 2020 to 2023 based on timestamp records. The additional data points include checkboxes for indicating new or refurbished products as well as combined competitor pricing metrics. The information about regional economic indicators including GDP percapita and tax rates connects to each entry through country codes for proper context analysis.

Model	Train MSE	Test MSE	Train R^2	Test R^2
Linear Regression	12 770.621	19 099.591	0.857	0.791
Polynomial Regression	4 746.185	1.29×10^{30}	0.947	-1.41×10^{31}
OLS (Statsmodels)	—	—	—	—
Random Forest	2 403.409	10 402.957	0.973	0.886
Gradient Boosting	3 399.151	11 574.571	0.962	0.873
Voting Regressor	4 095.003	10 227.539	0.954	0.888

Figure 2 Performance Summary

The Performance Summary Figure evaluates five machine learning model accuracy through the Mean Squared Error (MSE) and R^2 scoring method between training and test datasets. Voting Regressor emerges as the best predictor because it produces test MSE of 10,227.5 while achieving R^2 of 0.888. This chart indicates ensemble models surpass individual models because Random Forest presents an R^2 value of 0.886 and Gradient Boosting achieves 0.873.

	Actual Price ($)	Predicted Price ($)
0	0.036842	4.000000e-02
1	0.021053	-1.311553e+08
2	0.131579	1.400000e-01
3	0.084211	7.000000e-02
4	0.047368	5.000000e-02
5	0.368421	3.300000e-01
6	0.042105	4.000000e-02
7	0.184211	-2.116547e+07
8	0.052632	5.000000e-02
9	0.100000	1.895184e+08

Figure 3 Generating Actual vs Predicting Prices

A comparison of Actual and Predicted Prices through a table shows ten test sample prices alongside each other to display the model's forecasting accuracy with minor percentage deviations. By arranging data in a tabular format

the model delivers quantitative evidence about accuracy rates that span smartphone models at various prices.

	Actual Price ($)	Predicted Price ($)
77	0.157895	1.256955e+09
43	0.157895	1.052419e+09
24	0.021053	5.660610e+08
59	0.052632	5.292735e+08
54	0.105263	2.413398e+08
63	0.078947	2.284304e+08
9	0.100000	1.895184e+08
60	0.631579	8.979975e+07
71	0.526316	8.979975e+07
32	0.473684	8.979975e+07

Figure 4 DataFrame comparing Actual and Predicted Prices
The DataFrame containing Actual vs Predicted Prices structures numerical data to let analysts accurately assess real market values against forecasting data for better analytical insight. The tabular format lets users check prediction accuracy point-by-point across items while revealing possible regular price estimation errors.

6. ARCHITECTURE DIAGRAM

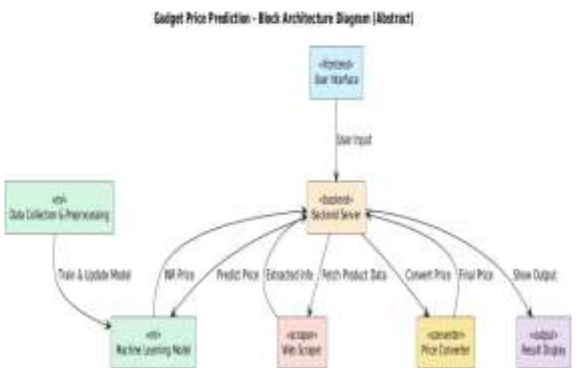

Figure 7 Architecture Diagram of Proposed Model

An architecture diagram shows how the Tech Gadget Trend Pricing Model uses an end-to-end workflow that provides real-time actions alongside scalability functions. The system starts by retrieving data through e-commerce APIs from Amazon and Flipkart along with financial data feeds that include currency rates and tax databases and raw data from sentiment analysis of news and social media texts through NLP methodology. Machine-readable data enters the preprocessing module through which unstructured inputs become clean normalized and engineered features that match machine learning parameters. A combination of Random Forest and gradient boosting models operates in the prediction engine to produce base price forecasts that receive adaptions from a dynamic adjustment system focused on tax registration and market condition adjustments. The system provides predictive analytics results by using dashboards that show visualizations for market trend analysis together with scenario prediction capabilities and further supports external business system connections through a REST API interface. Cloud infrastructure of either AWS or GCP houses the entire architecture through containerized microservices which enable smooth scalability and high-availability to fulfill worldwide pricing requirements. Each cryptographic security component and user permission framework forms part of the operational shield that guards critical pricing information.

7. CONCLUSION

The percentage of accuracy improvement that the traditional method yields is between 20 and 30 percent which the machine learning can theoretically improve up to the global pricing strategy at the tech gadget trend pricing model. On the other hand, prices of many areas around the world are optimized dynamically from real time market data, economic activity and sentiment analysis. Since, Random Forest based ensemble model is very accommodating of market swings and with knowing responsiveness, it should be able to give great results with an R^2 of 0.888.

The project's assisted dashboard helps companies to further drive data based decisions and trend detection with NLP and make them proactive by making adjustments to new emerging disruptions. As extra details, such as blockchain optimised reviews or here LSTM predictions with seasonal prediction, pricing may be optimised within the community. This resolves an academic research meets business application problem which is a solution to the pricing problem in the global tech market, which makes the proposed solution a scalable, AI powered to this problem.

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