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FULL LENGTH ARTICLE

Intelligent Stock Price Fusion in Mobile Industries

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ABSTRACT

In the tough cell phone business, guessing phone prices right is a key but hard job for new companies. Joining different types of information to look at stock prices may help, but we need strong ways to see how phone features and their costs tie together. This study aims to improve stock price analysis in the cell phone business by using data-fusion methods. The work looks for strong ties between many phone features, such as memory, camera details, and screen size, and how they affect price. To address this problem, careful work was performed to clean and prepare the information. Quadratic Discriminant Analysis (QDA) was then used, along with leading classifiers, to predict what will happen. Our findings demonstrate the QDA model's ability to detect subtle patterns and nonlinear correlations in the mobile phone dataset. The model's resilience and predictive ability are demonstrated through visualizations such as ROC AUC and Precision–Recall curves. Comparative analyses with current approaches highlight the higher performance of the suggested data-fusion approach. The use of QDA in data-fusion models demonstrates its versatility in capturing complicated interactions, resulting in nuanced insights into mobile phone price factors. This study adds an improved prediction framework for mobile phone price analysis, which is critical for new enterprises looking to gain a competitive advantage in the volatile mobile industry.

Keywords: Data fusion ▪ Mobile technology ▪ Predictive modeling ▪ Price estimation ▪ Machine learning ▪ Market dynamics ▪ Decision boundaries ▪ Market competitiveness

1. INTRODUCTION

Focusing on the fast-paced world of finance, understanding and forecasting stock prices play a key role in making investment choices and shaping market movement. The mobile industry, known for its quick changes and game-changing improvements, offers a tough yet hopeful place for investors and experts equally. Within the intricacies of this field, the use of smart computing emerges as a sturdy tool, providing ways to streamline stock price examination [1, 2, 3]. The blending of machine intelligence with stock price analysis starts a new era in financial models, especially for phone firms. By mixing machine learning, artificial intelligence (AI), and information-guided rules, we can now obtain a clearer view of how stock prices change over time [4]. This study examines how well these intelligent rules can help make better predictions about stock prices in phone companies [5, 6, 7, 8]. This study is important not only for investing, but also because it may help investors make better choices and keep markets stable for a long time [9, 10, 11]. Using machine intelligence can improve stock price analysis, reduce risks, simplify choices, and give investors more information when investing in phone companies [12, 13, 14, 15].

This paper takes a close look at how computers can help study changes in the value of mobile-company stocks. It combines knowledge from earlier research, theories about how markets work, and tools developed by practitioners. The goal is to add to what we know about using numbers to predict stock prices. It also encourages the adoption of new technologies to improve understanding of the stock market in the future.

This paper is organized step by step to explore how computers can help optimize the study of mobile-company stock prices. Section 2 reviews related studies. Section 3 explains the selected methodology. Section 4 describes the experimental design. Section 5 presents the results, and Section 6 concludes the paper.

2. RELATED WORKS

This section reviews key research studies and current projects. It combines and examines what is known from past works. King [16] provides detailed insights into how artificial intelligence is integrated into marketing strategies. The study highlights the importance of using AI tools to maintain a competitive advantage in a dynamic business environment and provides insights into how AI-driven processes can enhance decision-making and consumer autonomy. Li et al. [17] focus on the convergence of telecommunications technology and artificial intelligence in intelligent 5G. Their study examines potential synergies between cellular networks and AI and sheds light on how these developments can change network performance, efficiency, and capacity in the 5G era. Al-Blooshi and Nobanee [18] provide a brief but insightful review of artificial-intelligence applications in financial-management decision-making, including their contributions to financial analysis, risk analysis, and decision processes.

The authors of [19] conducted a bibliometric study examining the impact of artificial intelligence on branding strategies. The study provides an overview of developments and trends in the use of AI in branding practices, emphasizing its role in shaping brand positioning and consumer perceptions. The authors of [20] investigate the use of artificial intelligence to improve food quality through modeling methods. Their work examines the potential application of AI in food-industry processes, with the aim of improving product quality and overall food safety. Akerkar [21] offers a comprehensive exploration of artificial-intelligence applications in business. The study provides a holistic view of AI's role in optimizing business operations, decision-making, and strategy formulation, emphasizing its transformative potential across business sectors.

Thalore et al. [22] focus on the utilization of artificial intelligence in designing energy-efficient wireless sensor networks. Their study highlights AI-driven approaches to optimize network design, minimize energy consumption, and enhance network performance. Tang et al. [23] present a systematic review and co-citation network analysis of trends in artificial-intelligence-supported e-learning, emphasizing trends, advances, and implications for educational practice. Mishra and Tyagi [24] investigate the role of machine-learning techniques in Internet of Things (IoT)-based cloud applications, focusing on optimization and efficiency improvements. Salehi and Burgueño [25] explore emerging artificial-intelligence methods in structural engineering, while Kusiak [26] presents a comprehensive perspective on computational intelligence and data fusion in design and manufacturing.

3. METHODOLOGY

This section presents a comprehensive framework detailing the methodical processes, computational models, and analytical techniques employed in this study. The use of data-fusion techniques in financial analysis, particularly in the context of mobile companies, demands a structured and meticulous approach.

Prior to model training, a series of preprocessing steps were systematically implemented to cleanse and prepare the dataset for robust analysis and model development. The initial phase involved a comprehensive examination for missing values, outliers, and inconsistencies. Missing data points were addressed through imputation strategies using mean, median, or mode values for numerical features, while categorical features underwent imputation using their most frequent values [12]. Outliers, identified using statistical methods such as z-scores or interquartile ranges, were either corrected or removed according to their impact on data distribution and model performance. A normalization and scaling process was then used to standardize numerical features, ensure uniformity, and mitigate the influence of feature-magnitude discrepancies on model training. Categorical variables were transformed into numerical representations using techniques such as one-hot or label encoding. Feature engineering was applied to extract or create new variables and improve the dataset's informative capacity. Finally, correlation analysis, recursive feature elimination, and domain-knowledge-driven selection were considered to curate a refined set of features while mitigating dimensionality issues [14].

The QDA algorithm, a classical and robust classification technique, is a pivotal component of the predictive-modeling framework for mobile-phone price analysis. QDA operates on the foundational principles of discriminant analysis, aiming to identify decision boundaries between classes by modeling the probability distributions of features within each class. Unlike Linear Discriminant Analysis (LDA), QDA relaxes the assumption of equal covariance matrices among classes and permits a distinct covariance structure for each class. This approach accommodates scenarios in which classes exhibit varying degrees of variance and covariance, enabling QDA to capture nonlinear decision boundaries more effectively than linear models.

The fundamental principle of QDA involves estimating class-specific Gaussian distributions, characterized by their mean vectors and covariance matrices. Leveraging Bayes' theorem, QDA calculates posterior probabilities for class membership from the likelihood of observing the features given each class and the prior probabilities of class occurrence:

$$\begin{aligned} P(y=k \mid \mathbf{x}) &= \frac{P(\mathbf{x} \mid y=k)P(y=k)}{P(\mathbf{x})} \\ &= \frac{P(\mathbf{x} \mid y=k)P(y=k)}{\sum_l P(\mathbf{x} \mid y=l)P(y=l)}. \end{aligned} \tag{1}$$

The primary theory underpinning QDA lies in the formulation of quadratic decision boundaries. Each decision boundary represents a quadratic surface, allowing greater flexibility in capturing complex class boundaries than linear models. The class-conditional Gaussian density is

$$P(\mathbf{x} \mid y=k) = \frac{1}{(2\pi)^{d/2}|\Sigma_k|^{1/2}} \times \exp\left[-\frac{1}{2}(\mathbf{x}-\mu_k)^T\Sigma_k^{-1}(\mathbf{x}-\mu_k)\right]. \tag{2}$$

This flexibility allows QDA to capture intricate relationships and nonlinear patterns in the dataset. By accommodating a different covariance matrix for each class, QDA adapts to datasets whose classes exhibit distinct variance–covariance structures. The log-posterior probability used for classification can be written as

$$\begin{aligned}\log P(y=k \mid \mathbf{x}) &= \log P(\mathbf{x} \mid y=k) + \log P(y=k) + C \\ &= -\frac{1}{2}\log|\Sigma_k| - \frac{1}{2}(\mathbf{x}-\mu_k)^T\Sigma_k^{-1}(\mathbf{x}-\mu_k) \\ &\quad + \log P(y=k) + C.\end{aligned} \tag{3}$$

4. EXPERIMENTAL DESIGN

To assess the efficacy and performance of the data-fusion models applied to mobile-industry stock price analysis, a multifaceted evaluation strategy was adopted. Accuracy measures the overall correctness of predictions against actual price movements. Recall and precision measure the model's ability to identify positive cases and minimize false positives, respectively. The F1-score balances precision and recall through their harmonic mean. In addition, Kappa statistics assess agreement between predicted and observed values while accounting for agreement that may occur by random chance. Together, these measures provide a comprehensive understanding of the models' predictive capabilities and real-world applicability.

The dataset used in the experiments was compiled for a mobile company's price-estimation problem and contains diverse attributes associated with mobile phones and their selling prices. The available features include RAM, internal memory, and other technical specifications that define mobile-phone functionality. These attributes represent characteristics that may influence market value, while the `price_range` column serves as the target variable. Advanced analytical methods are therefore applied to derive meaningful relationships between the mobile-phone attributes and their corresponding market values. Table 1 outlines the hardware and software used for implementation.

Table 1. Hardware and software specifications for data-fusion implementation.

Aspect	Description
Hardware	
Processor	Intel Core i7-10700K, 8-core, 3.8 GHz
RAM	32 GB DDR4
Graphics Card	NVIDIA GeForce RTX 3080, 10 GB
Storage	1 TB NVMe SSD (Solid State Drive)
Software	
Operating System	Windows 10 Professional
Programming Languages	Python (version 3.8)
Machine Learning	TensorFlow, PyTorch, Scikit-learn
Data Processing	Pandas, NumPy, Matplotlib
Development IDE	Jupyter Notebook, PyCharm

5. RESULTS AND DISCUSSION

The application of data-fusion methodologies to mobile-industry stock price analysis yields a diverse array of results for examination. This section discusses the empirical outcomes derived from the implemented models and analytical frameworks, with attention to predictive performance and practical implications within the dynamic landscape of mobile corporations.

Figure 1 presents a correlation map of the stock-price determinants. The target price range exhibits a notably strong positive correlation with RAM, signifying that the selling price of mobile phones tends to rise as RAM capacity increases. The map also shows a positive correlation between 3G and 4G technologies, underscoring their interdependence in influencing mobile-phone prices. Similarly, the correlation between primary-camera resolution (`pc`) and front-camera resolution (`fc`) indicates the collective impact of camera specifications on price determination. The relationships between pixel-resolution width (`px_width`) and height (`px_height`), and between screen width (`sc_w`) and height (`sc_h`), demonstrate the importance of cohesive technical specifications in determining mobile-phone prices.

Table 2 compares the proposed data-fusion model with state-of-the-art methodologies. A robust five-fold cross-validation method is used to examine the efficacy of the proposed model against contemporary approaches. This benchmarking exercise makes it possible to identify the strengths, limitations, and distinctive predictive capabilities of the proposed model while assessing generalizability, reliability, and possible overfitting.

The integration of QDA within the data-fusion model is a pivotal factor contributing to substantial enhancements in predictive performance compared with alternative classifiers. QDA's capacity to handle nonlinear relationships and complex interactions among variables yields notable improvements in discerning intricate patterns within the mobile-phone dataset. Its ability to model class boundaries flexibly and accurately, especially when the data distributions exhibit nonlinearity, leads to enhanced predictive capability. The superior performance achieved by QDA underscores its suitability for stock price analysis in the mobile industry.

Figure 2 presents the Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) metric for QDA. This visualization depicts the model's ability to distinguish among the price-range classes in the mobile-phone dataset. A larger AUC value indicates a greater capacity to identify price-movement classes correctly and illustrates QDA's effectiveness in capturing diverse patterns and relationships among mobile-phone features.

Figure 3 shows the QDA model's precision–recall trade-off. Changes in the classification threshold affect both precision and recall, illustrating the model's ability to identify positive cases accurately while capturing the relevant instances in the dataset. The curve therefore provides a nuanced view of the

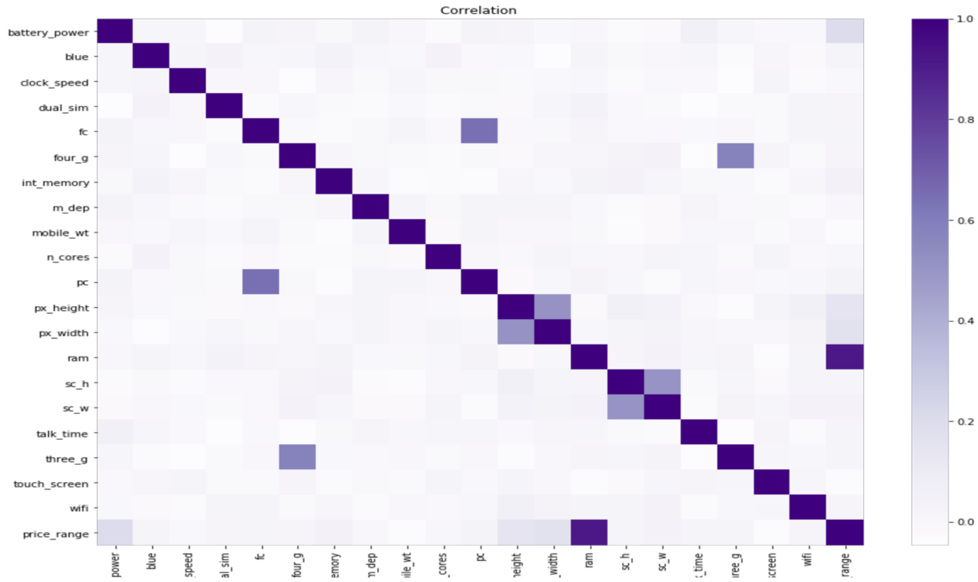

Figure 1. Correlation map of mobile-phone features and price range.

Table 2. Comparative analysis of predictive performance between the proposed data-fusion model and state-of-the-art approaches using five-fold cross-validation.

Model	Accuracy	Recall	Prec.	F1	Kappa
Decision Tree Classifier	0.4562	0.4562	0.4944	0.4378	0.2750
Ridge Classifier	0.5806	0.5806	0.6525	0.4909	0.4408
Random Forest Classifier	0.5806	0.5806	0.5717	0.5710	0.4408
K Neighbors Classifier	0.5850	0.5850	0.6032	0.5872	0.4467
Extra Trees Classifier	0.6956	0.6956	0.6860	0.6803	0.5942
Gradient Boosting Classifier	0.7019	0.7019	0.6962	0.6967	0.6025
Ada Boost Classifier	0.7062	0.7062	0.7027	0.7029	0.6083
Extreme Gradient Boosting	0.7088	0.7088	0.7007	0.7014	0.6117
Light Gradient Boosting Machine	0.7219	0.7219	0.7189	0.7188	0.6292
Linear Discriminant Analysis	0.7463	0.7463	0.7466	0.7226	0.6617
Naive Bayes	0.7563	0.7563	0.7516	0.7485	0.6750
CatBoost Classifier	0.7687	0.7688	0.7652	0.7653	0.6917
SVM – Linear Kernel	0.7694	0.7694	0.7688	0.7649	0.6925
Logistic Regression	0.8481	0.8481	0.8450	0.8428	0.7975
Quadratic Discriminant Analysis	0.9219	0.9219	0.9233	0.9207	0.8958

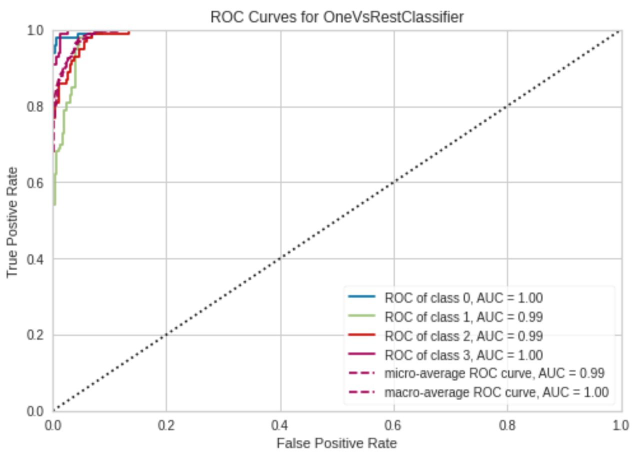

Figure 2. ROC AUC curves for QDA in mobile-phone price prediction.

model's capacity to balance these two measures.

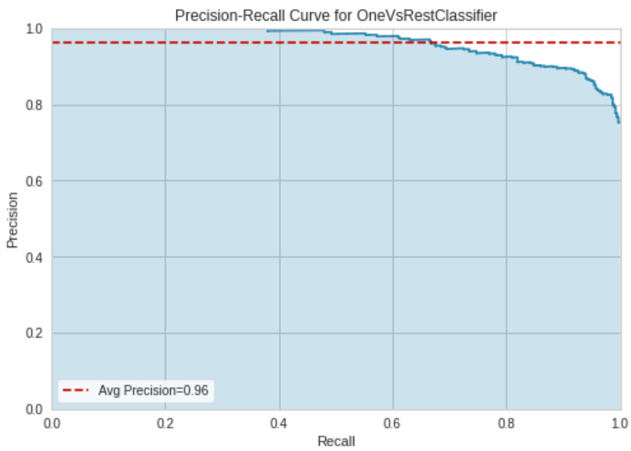

Figure 3. Precision–Recall curve for QDA in mobile-phone price prediction.

Figure 4 visualizes the classification report and presents a detailed breakdown of the QDA model's precision, recall, F1-score, and support for each class. The report provides granular insight into performance for different price-range categories, highlights strengths and areas for improvement, and contributes to a holistic assessment of predictive capability.

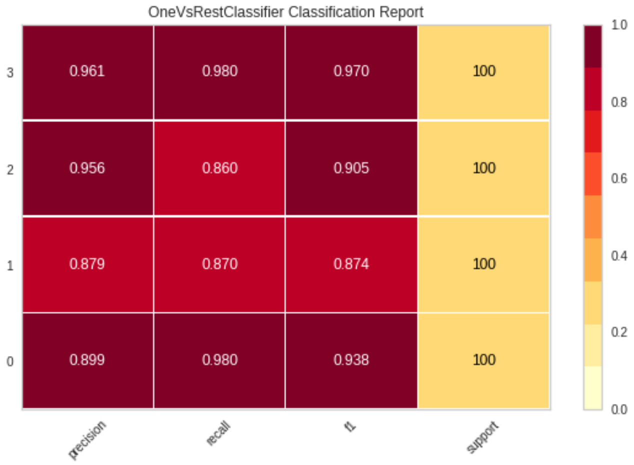

Figure 4. Classification-report visualization for QDA in mobile-phone price prediction.

Figure 5 depicts learning curves for the training and validation datasets as a function of training size. The convergence or divergence of these curves provides insight into the model's bias–variance trade-off, its ability to learn from additional training instances, and its ability to generalize to unseen samples. The figure is therefore a useful diagnostic for assessing the model's learning dynamics and scalability.

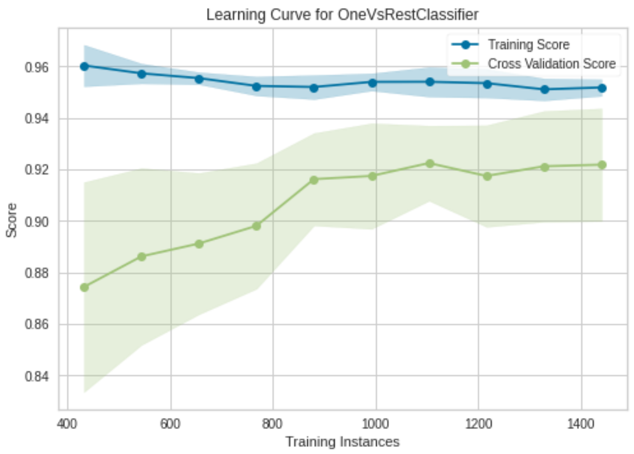

Figure 5. Learning curves depicting model performance across training and validation datasets for QDA in mobile-phone price prediction.

6. CONCLUSION AND FUTURE WORK

In the dynamic landscape of the mobile industry, this study explored data fusion for advanced stock price analysis, aiming to decipher the intricate interplay between mobile-phone features and their market values. Through meticulous preprocessing and the application of Quadratic Discriminant Analysis within a data-fusion framework, the research revealed important relationships shaping mobile-phone prices. The efficacy of QDA in capturing nonlinear patterns and discerning complex decision boundaries emerged as a cornerstone, demonstrating its adaptability in this domain.

Comparative analyses against state-of-the-art classifiers underscored the superiority of the data-fusion approach and affirmed its capability in price prediction for mobile companies striving for market competitiveness. The amalgamation of data-fusion techniques and QDA provides a refined predictive framework for navigating the challenges of price analysis in the mobile industry. The identified relationships between mobile-phone attributes and pricing dynamics offer actionable insights that can support emerging companies in product development and market positioning. As mobile technology continues to evolve, advanced computational methods can improve price-estimation accuracy, foster a deeper understanding of market trends, and propel mobile companies toward sustainable growth and competitive advantage.

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