



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 info to look at stock prices may help, but we need strong ways to see how phone things and their costs tie together. This study wants to make stock price checking better in the cell phone busine-ss by using ways to join info. The work looks for strong ties between many phone things like memory, camera details, and screen size and how they affect the price. To fix this, very careful work was done to clean and fix the info. The Quadratic Discriminant Analysis rule- was then used, along with top classifiers, for saying what will happen. Our findings demonstrate the QDA model's ability to detect subtle patterns and nonlinear correlations in the mobile phone data set. 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 investme-nt 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 e-xperts equally. Within the intricacies of this field, the use of smart computing pops up as a sturdy tool, lending ways to streamline stock price examination [1-3]. The blending of machine smarts with stock price checking starts a new time in monetary models, especially for phone firms. By mixing learning machines, AI, and information guided rules, we can now get a clearer view of how stock prices change over time [4]. This study tries to see how well these machine smart rules can help make better guesses about stock prices in phone companies [5-8]. Rephrase. This study is important not just for inve-sting but also because it may help inve-stors make better choices and keep markets stable- for a long time [9-11]. Using machine smarts can help fix how we check stock prices and possibly cut risks, make choices easier, and give inve-stors more facts when putting their money in phone companies [12-15].

This paper takes a close look at how computers can help study change-s in the value of mobile company stocks. It combines things researchers have- learned, theories about how markets work, and tools people have- made. The goal is to add to what we know about using numbers to predict stock prices. It also wants people- to use new technologies more to help understand the stock market better in the future.

This paper is organized step-by-step to explore fully how computers can help optimize studying mobile company stock prices. Section two reviews many re-lated studies. Section three explains carefully the method chosen. Section

four de-scribes in detail how the experiment will be done-. Section five is where- the results are shown. Finally, section six pulls together what was found.

2. Related Works

This section re-views key rese-arch studies and current projects. It combines and examines what we know from past works. King [16] provides detailed insights into how artificial intelligence (AI) is integrated into marketing strategies. The study highlights the importance of using AI tools to maintain a competitive advantage in the dynamic business environment and provides insights into how AI-driven processes can enhance decision-making processes and consumer autonomy will be included has improved Lee et al. [17] In telecommunications, smart 5G focuses on the convergence of technology and artificial intelligence. This study examines the potential synergies between cellular networks and AI, and sheds light on how these developments can change network performance, performance, and capacity in the 5G era Al-Blushi and Nobani [18] provide a brief but insightful review in artificial intelligence applications in financial management decision making -Technology contributes to financial analysis, risk analysis, and decision-making processes in finance. The authors of [19] conducted a careful bibliometric study, examining the impact of artificial intelligence on branding strategies. This study provides an overview of the developments and trends in the use of AI in branding practices, emphasizing its role in shaping, and influencing brand positioning and consumer perceptions. The authors of [20] investigate the use of artificial intelligence to improve nutrition through modeling methods. This study examines the potential application of AI in food industry processes, with the aim of improving product quality, product quality and overall food safety. Akerkar [21] offers a comprehensive exploration of artificial intelligence applications in the business domain. The study provides a holistic view of AI's role in optimizing business operations, decision-making, and strategy formulation, emphasizing its transformative potential across various business sectors. Thalore et al. [22] focus on the utilization of artificial intelligence in designing energy-efficient wireless sensor networks. This study highlights AI-driven approaches to optimize network design, aiming to minimize energy consumption and enhance network performance in wireless sensor applications. Tang et al. [23] present a systematic review and co-citation network analysis of trends in artificial intelligence-supported e-learning. This study provides a comprehensive overview of AI's integration in educational contexts, emphasizing trends, advancements, and implications for e-learning practices. Mishra and Tyagi [24] investigate the role of machine learning techniques in Internet of Things (IoT)-based cloud applications. The study explores how machine learning algorithms contribute to enhancing IoT-based cloud applications, focusing on optimization and efficiency improvements. Salehi and Burgueño [25] explore emerging artificial intelligence methods in structural engineering. This study delves into AI-driven approaches to improve structural engineering practices, aiming to enhance efficiency, reliability, and innovation in structural design and analysis. Kusiak [26] presents a comprehensive perspective on data fusion in design and manufacturing. This study provides a holistic view of data fusion applications, emphasizing its role in optimizing design and manufacturing processes across diverse industries.

3. Methodology

This section presents a comprehensive framework detailing the methodical processes, computational models, and analytical techniques employed in this study. The utilization 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 meticulous 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 within the dataset. Any missing data points were addressed through imputation strategies, considering mean, median, or mode values for numerical features, while categorical features underwent the imputation of most frequent values [12]. Outliers, identified using statistical methods such as z-scores or interquartile ranges, were either corrected or removed based on their impact on data distribution and model performance. Following this, a stringent normalization and scaling process was enacted to standardize numerical features, ensuring uniformity, and mitigating the influence of feature magnitude discrepancies on model training. Categorical variables underwent encoding processes, transforming them into numerical representations suitable for model comprehension, often through techniques like one-hot encoding or label encoding. Moreover, feature engineering techniques were applied to extract or create new features, amplifying the dataset's informative capacity and potentially enhancing model predictive power. Finally, a comprehensive feature selection process was undertaken, utilizing methodologies like correlation analysis, recursive feature elimination, or domain knowledge-driven selection, to curate a refined set of features optimized for model training while mitigating dimensionality issues. This sequence of preprocessing steps laid the groundwork for a clean, standardized, and optimized dataset, essential for training robust data fusion models for mobile phone price prediction [14].

The QDA algorithm, a classical and robust classification technique, stands as a pivotal component in our predictive modeling framework for mobile phone price analysis. QDA operates on the foundational principles of discriminant analysis, aiming to discern decision boundaries between different classes by modeling the probability distributions of features within each class. Unlike its counterpart, Linear Discriminant Analysis (LDA), QDA relaxes the assumption of equal covariance matrices among classes, allowing for distinct covariance structures for each class. This approach caters to scenarios where the classes exhibit varying degrees of variance and covariance, enabling QDA to capture non-linear decision boundaries more effectively than linear models. The fundamental principle of QDA involves estimating class-specific Gaussian distributions for each feature, characterized by their mean vectors and covariance matrices. Leveraging Bayes' theorem, QDA calculates posterior probabilities for class membership based on the likelihoods of observing features given each class and the prior probabilities of class occurrence. The fundamental premise underlying both Linear Discriminant Analysis (LDA) and QDA revolves around probabilistic models that characterize the class conditional distribution of the data. These models aim to capture the probability distributions of features given each class, allowing for the estimation of the likelihood of observing specific features within a particular class. By assuming different distributions for each class, LDA and QDA diverge in their treatment of the covariance matrices within these distributions.

$$P(y = k|x) = \frac{P(x|y=k)P(y=k)}{P(x)} = \frac{P(x|y=k)P(y=k)}{\sum_l P(x|y=l) \cdot P(y=l)} \quad (1)$$

The primary theory underpinning QDA lies in the formulation of quadratic decision boundaries, resulting from the consideration of quadratic functions to model the relationship between features and classes. Each decision boundary represents a quadratic surface, allowing for greater flexibility in capturing complex decision boundaries compared to linear models.

$$P(x|y = k) = \frac{1}{(2\pi)^{\frac{d}{2}} |\Sigma_k|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x - \mu_k)^t \Sigma_k^{-1} (x - \mu_k)\right) \quad (2)$$

This flexibility in boundary shaping permits QDA to capture intricate relationships and non-linear patterns inherent in the dataset, essential for nuanced price prediction in the diverse mobile phone market. Moreover, by accommodating differing covariance matrices for each class, QDA offers adaptability in handling datasets where classes exhibit distinct variance-covariance structures, contributing to its robustness in classification tasks. The log of the posterior probability, as described in the model, serves as a fundamental component in Bayesian inference and classification tasks. In the context of the model, the log of the posterior probability can be mathematically represented as the natural logarithm of the posterior probability itself. It can be calculated using Bayes' theorem, which involves the prior probability of a class (probability of observing any data) multiplied by the likelihood of observing the data given that class, divided by the evidence (probability of observing the data across all classes).

$$\log P(y = k|x) = \log P(x|y = k) + \log P(y = k) + Cst = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^t \Sigma_k^{-1} (x - \mu_k) + \log P(y = k) + Cst \quad (3)$$

4. Experimental Design

In assessing the efficacy and performance of the data fusion models applied to optimize stock price analysis in the mobile industry, a multifaceted evaluation strategy encompassing various metrics has been adopted. Accuracy serves as a fundamental measure, gauging the overall correctness of predictions against actual stock price movements. Recall and Precision metrics offer a nuanced understanding of the model's performance concerning correctly identifying positive cases and minimizing false positives, respectively. F1 score strikes a balance between precision and recall, capturing the harmonic mean to assess the overall model accuracy. Additionally, Kappa statistics provide an assessment of the agreement between predicted and observed values, considering the possibility of random chance, thereby offering a robust measure of model performance while accounting for chance agreement beyond what might be expected by random classification. The utilization of these diverse evaluation measures aims to holistically assess the data fusion models' effectiveness in optimizing stock price analysis within the mobile sector, providing a comprehensive understanding of their predictive capabilities and real-world applicability.

The dataset used in our experiments is compiled by Bob for his mobile company's price estimation conundrum encapsulates diverse attributes associated with mobile phones and their respective selling prices. As Bob aims to establish a competitive edge in the mobile market, he has gathered a comprehensive array of features, including but

not limited to RAM, internal memory, and potentially other technical specifications defining mobile phone functionalities. These attributes, akin to the 'Rooms', 'Type', 'Distance', 'Bedroom2', 'Bathroom', and 'Car' columns in the dataset, represent key characteristics of mobile phones that could potentially influence their market value. Bob's intention to discern correlations between these phone features and selling prices echoes in the 'Price' column, which serves as the target variable for price estimation. However, Bob's lack of expertise in machine learning necessitates the exploration and application of advanced analytical methodologies to derive meaningful relationships between these mobile phone attributes and their corresponding market values. In addition, Table 1 outlines the details of the hardware and software specifications for the implementation setups.

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 10GB
Storage	1TB 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 culmination of data fusion methodologies applied to optimize stock price analysis within the mobile industry yields a diverse array of results ripe for meticulous examination and comprehensive discussion. This section elucidates the empirical outcomes derived from the implemented models and analytical frameworks, shedding light on their efficacy, predictive performance, and practical implications within the dynamic landscape of mobile corporations. In Figure 1, the correlation map illuminates crucial insights pertinent to our analysis of stock price determinants within the mobile industry. Notably, the target price range exhibits a notably strong positive correlation with RAM, signifying that as RAM capacity increases, the selling price of mobile phones tends to rise correspondingly. Furthermore, the correlation map unveils intriguing relationships among various technical specifications: a distinct 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) showcases a positive association, hinting at the collective impact of camera specifications on price determination. Additionally, the link between pixel resolution width (px_weight) and pixel resolution height (px_height), as well as the correlation between screen width (sc_w) and screen height (sc_h), signifies the importance of cohesive specifications in determining mobile phone prices, reflecting the market's responsiveness to harmonized technical attributes across these dimensions. These observations gleaned from the correlation map provide valuable insights into the relationships between specific mobile phone features, accentuating their collective influence on pricing dynamics within the mobile industry.

In Table 2, a comparative analysis between the proposed data fusion model and state-of-the-art methodologies reveals a comprehensive evaluation of predictive performance within the realm of stock price analysis for mobile phones. Employing a robust 5-fold cross-validation methodology, our study meticulously examines the efficacy of the proposed data fusion model against contemporary approaches. This comparative analysis serves as a crucial benchmarking exercise, allowing us to discern the strengths, limitations, and distinctive predictive capabilities of our proposed model in forecasting mobile phone prices. By subjecting the models to rigorous cross-validation experiments,

we ensure a robust assessment of their generalizability and reliability, providing a comprehensive understanding of their performance across diverse datasets and mitigating potential biases or overfitting tendencies. This comparative analysis in Table 2 offers valuable insights into the competitiveness and efficacy of our proposed data fusion model, positioning it within the landscape of cutting-edge methodologies for stock price prediction within the dynamic mobile industry.

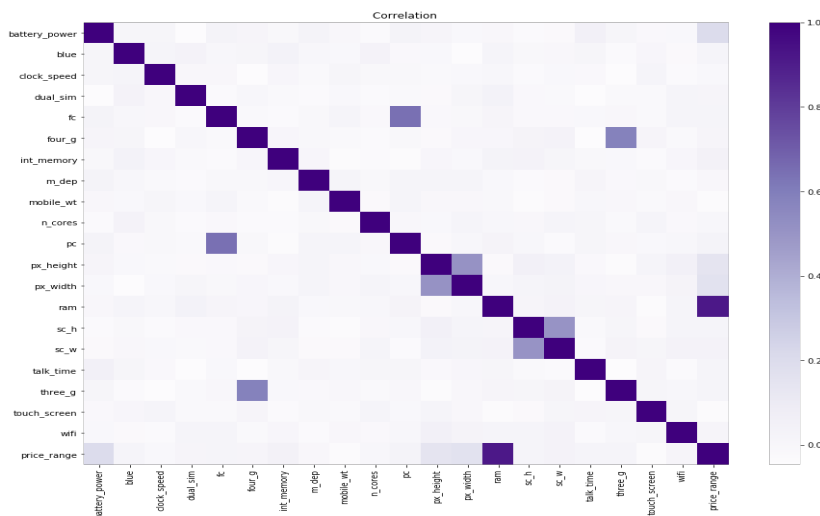


Figure 1: Correlation Map of Mobile Phone Features and Price Range

Table 2: Comparative Analysis of Predictive Performance between Proposed data fusion Model and State-of-the-Art Approaches via 5-Fold Cross-Validation Experiments.

Model	Accuracy	Recall	Prec.	F1	Kappa
Decision Tree Classifier	0.4562	0.4562	0.4944	0.4378	0.275
Ridge Classifier	0.5806	0.5806	0.6525	0.4909	0.4408
Random Forest Classifier	0.5806	0.5806	0.5717	0.571	0.4408
K Neighbors Classifier	0.585	0.585	0.6032	0.5872	0.4467
Extra Trees Classifier	0.6956	0.6956	0.686	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	0.675
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	0.845	0.8428	0.7975
Quadratic Discriminant Analysis	0.9219	0.9219	0.9233	0.9207	0.8958

The integration of QDA within our data fusion model stands out as a pivotal factor contributing to substantial enhancements in predictive performance compared to alternative classifiers. The utilization of QDA, known for its capacity to handle non-linear relationships and complex interactions among variables, yielded notable improvements

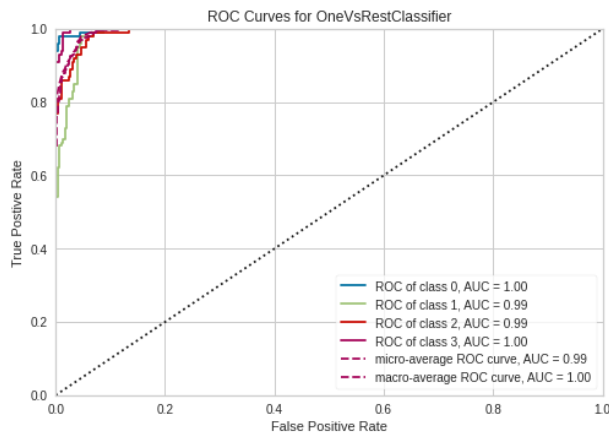


Figure 2: ROC AUC Curve for QDA in Mobile Phone Price Prediction

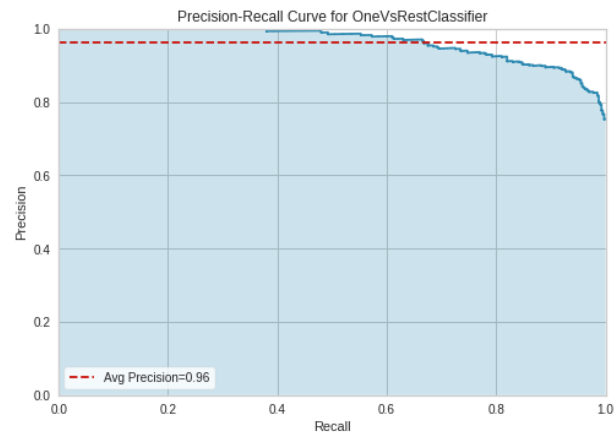


Figure 3: Precision-Recall Curve for QDA in Mobile Phone Price Prediction

in discerning intricate patterns within the mobile phone dataset. Its inherent ability to model class boundaries more flexibly and accurately, especially in scenarios where data distributions exhibit non-linearity, resulted in enhanced predictive capabilities. This augmentation led to discernible advancements in predictive accuracy, demonstrating QDA's efficacy in capturing nuanced relationships among mobile phone features and their corresponding prices. The superior performance achieved by QDA compared to other classifiers underscores its suitability and effectiveness within the context of stock price analysis in the mobile industry, reaffirming its role as a cornerstone in optimizing predictive models for this domain.

Figure 3 presents a graphical representation of the Receiver Operating Characteristic (ROC) curve, specifically showcasing the Area Under the Curve (AUC) metric for QDA. This visualization serves as a comprehensive depiction of the QDA model's performance in distinguishing between different price movement classes within the mobile phone dataset. The ROC AUC curve offers a holistic assessment of the model's discriminatory power and its ability to accurately classify various price range categories. As the curve's area underlines, a larger AUC value signifies the model's superior capacity in correctly identifying price movement classes, thereby illustrating QDA's effectiveness in capturing diverse patterns and relationships inherent in mobile phone features vis-à-vis their respective prices. This

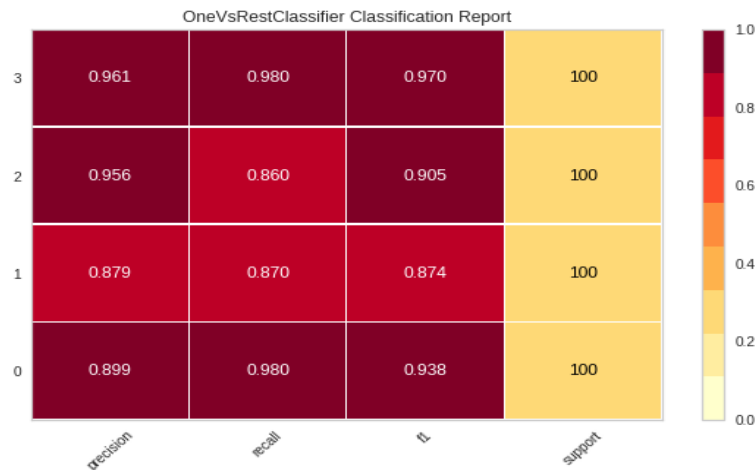


Figure 4: Classification Report Visualization for QDA in Mobile Phone

graphical representation in Figure 2 provides a clear and concise depiction of the QDA model's predictive prowess, offering insights into its robustness and discriminatory accuracy in stock price analysis within the dynamic landscape of the mobile industry.

In Figure 3, the Precision-Recall curve visualization offers a comprehensive portrayal of the Quadratic Discriminant Analysis (QDA) model's precision-recall trade-off within the context of mobile phone price prediction. This graphical representation delineates the intricate balance between precision and recall metrics, crucial in evaluating the model's

performance across varying thresholds. By showcasing how changes in the classification threshold impact the precision and recall values, this curve illustrates the QDA model's ability to accurately identify positive cases (precision) while effectively capturing all relevant instances (recall) within the dataset. The Precision-Recall curve in Figure 3 provides a nuanced understanding of the QDA model's performance, offering insights into its capacity to balance precision and recall, essential in discerning its suitability for stock price prediction in the mobile industry.

Figure 4 encapsulates the comprehensive visualization of the classification report, presenting a detailed breakdown of the QDA model's performance across various classification metrics. This report offers an inclusive overview encompassing precision, recall, F1-score, and support for each class within the dataset. By providing granular insights into the model's performance for different price range categories, the classification report in Figure 4 facilitates a comprehensive understanding of the QDA model's predictive accuracy, highlighting its strengths and areas for improvement. This visualization serves as a valuable tool in assessing the model's effectiveness in distinguishing between price movement classes within the mobile phone dataset, offering a detailed breakdown of its performance metrics for each class and contributing to a holistic evaluation of its predictive capabilities in stock price analysis within the mobile industry.

In Figure 5, the depiction of learning curves offers a comprehensive insight into the QDA model's performance concerning training and validation datasets as a function of the training size. This visualization illustrates the model's learning behavior, showcasing its capability to generalize from available data and its sensitivity to varying dataset sizes. By observing the convergence or divergence of the training and validation curves over iterations, these learning curves provide valuable insights into the model's bias-variance trade-off. They showcase how the model's performance evolves with additional training instances, shedding light on its ability to learn from data and generalize to unseen samples. Figure 5 serves as a crucial diagnostic tool, aiding in the assessment of the model's learning dynamics and scalability, offering insights into its capacity to handle different data volumes effectively within the domain of mobile phone price prediction.

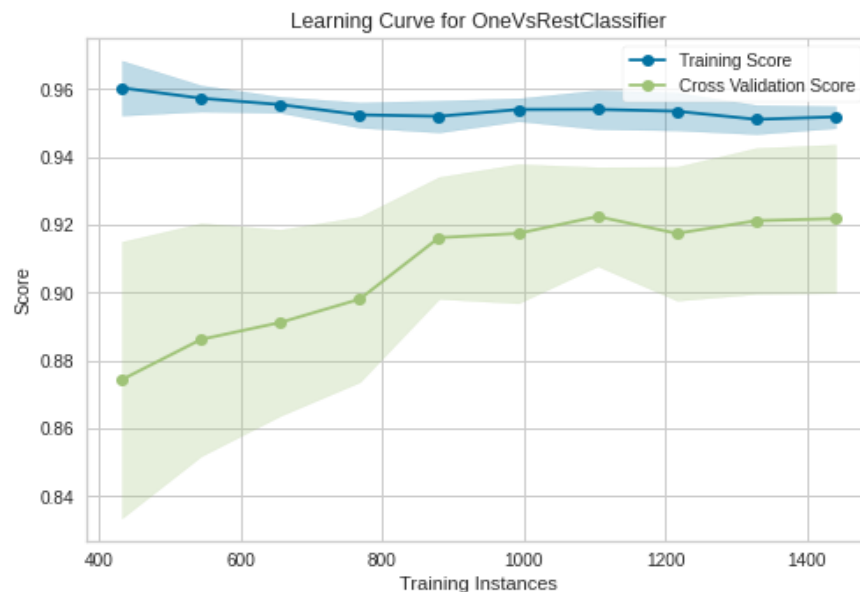


Figure 5: Learning Curves depicting Model Performance across Training and Validation Datasets for QDA in Mobile Phone Price Prediction

6. Conclusion and Future work

In the dynamic landscape of the mobile industry, this study delved into the realm of 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 (QDA) within a data fusion

framework, this research revealed profound insights into the nuanced relationships shaping mobile phone prices. The efficacy of QDA in capturing non-linear patterns and discerning complex decision boundaries emerged as a cornerstone, showcasing its adaptability in this domain. Comparative analyses against state-of-the-art classifiers underscored the superiority of our data fusion approach, affirming its prowess in price prediction for mobile companies striving for market competitiveness. The amalgamation of data fusion techniques and QDA has unveiled a refined predictive framework crucial for navigating the challenges of price analysis in the mobile industry. The identified relationships between mobile phone attributes and pricing dynamics offer actionable insights, empowering emerging companies to make informed decisions in product development and market positioning. As mobile technology continues to evolve, the utilization of advanced computational methodologies not only enhances price estimation accuracy but also fosters a deeper understanding of market trends, propelling mobile companies towards sustainable growth and competitive advantage in this ever-evolving landscape.

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