AAI2002 ITP MIDTERM REPORT

AOP - Asset Owner Platform

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ABSTRACT

This project aims to enhance data-driven decision-making in Singapore's real estate market through the development of the Asset Owner Platform with AI. The platform integrates predictive analytics and cloud-based infrastructure to deliver accurate forecasts for property prices, market trends, rental yields, and housing demand. Using historical HDB resale data from 1990 onwards, various machine learning models such as XGBoost, Long Short-Term Memory (LSTM) and ARIMA were developed and compared based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). XGBoost emerged as the most consistent and scalable model across multiple tasks, balancing performance with efficiency. LSTM demonstrated strength in temporal pattern recognition, while ARIMA served as a baseline for one-variable forecasts. The system is to be deployed using Amazon Web Services (AWS), with MLflow enabling model tracking and version control. Visual analytics are also integrated to highlight pricing trends and regional market insights. The results support the platform's goal of empowering property owners, developers and investors with intelligent tools for valuation, bidding and strategic planning.

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1. BACKGROUND

The Asset Owner Platform with AI project is an advanced real estate analytics system designed to revolutionize property investment decision-making. This platform integrates AI-driven predictive analytics, automated valuation models, and real-time market insights to empower property owners, investors and stakeholders with data-backed recommendations [1]. In alignment with HDB Place2Lease, which facilitates the rental of HDB commercial properties and short-term stays, the Asset Owner Platform extends its capabilities by providing deeper analytical insights into property leasing trends, rental demand forecasting, and price optimization [2]. This ensures that users can evaluate market conditions, anticipate fluctuations in rental demand, and optimize asset utilization more effectively (Refer to Fig. 1) [3].

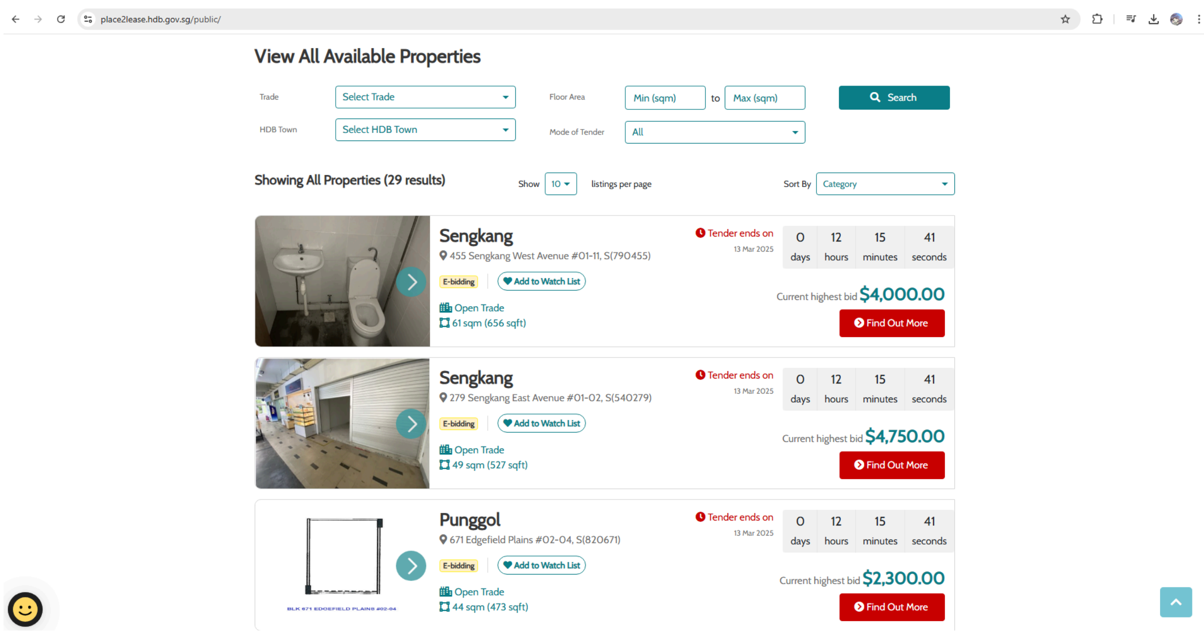

Figure 1. HDB Place2Lease Website

1.1 Key Features and Objectives

The primary goal of this project is to provide an intelligent e-Bidding Engine that facilitates real-time auctions for both B2B and B2C property transactions. By leveraging AI, the platform enhances property sales and rental processes through automated valuation models, demand forecasting, and predictive price analytics. The system also supports NLP-based chatbots for customer inquiries, text analysis for property reviews, and automated contract generation [1].

1.1.1 Predictive Price Analytics

The platform incorporates AI-powered predictive price analytics to estimate property values dynamically, reducing valuation errors and enhancing pricing accuracy [1]. Machine learning models process extensive historical transaction data, location-based metrics, and economic indicators to provide real-time price estimations. The integration of AI-driven valuation methods ensures that properties listed for bidding reflect market trends, minimizing risks for buyers and sellers alike. Furthermore, the system continuously updates price predictions based on new transactions, interest rates, and inflation trends, allowing investors to make informed financial decisions during bidding processes.

1.1.2 Market Trend Analysis

Detects shifts in the real estate market, helping property owners make informed decisions [1]. AI-driven trend analysis can highlight emerging hotspots, assess the impact of economic changes, and detect seasonal price fluctuations [4]. Additionally, the platform can provide visual analytics and alerts on property market movements, enabling users to adapt their investment strategies proactively [5]. Through sentiment analysis of real estate news and online discussions, the system can identify patterns that influence property demand, further improving market forecasting accuracy [6].

1.1.3 Rental Yield Prediction

The system evaluates potential rental returns by analyzing rental price trends, occupancy rates, and macroeconomic conditions [1]. AI models integrate real-time rental listings, demographic data, and inflation-adjusted rental growth to generate precise rental yield predictions. This allows property owners and investors to estimate rental income potential accurately before purchasing or leasing properties [7]. The platform also incorporates risk assessment metrics, identifying factors such as vacancy periods and tenant demand fluctuations that impact rental profitability. Additionally, the automated valuation models adjust rental yield estimations dynamically, ensuring accurate financial projections for asset owners.

1.1.4 Demand Forecasting

AI-powered demand forecasting enables property developers and investors to anticipate housing demand fluctuations over different time horizons. By analyzing demographic shifts, migration trends, and employment data, the system predicts future property demand across various locations [8]. This feature supports optimal inventory planning, ensuring that real estate supply aligns with market needs to prevent oversupply or undersupply scenarios. The platform also utilizes real-time auction participation data to assess demand trends dynamically, enabling asset owners to adjust bidding strategies accordingly. By incorporating AI-driven forecasting, the e-Bidding Engine ensures that property stakeholders make data-driven investment decisions that align with future market trends.

1.2 Current Architecture and Deployment

The platform is built using a modern microservices architecture. Its frontend utilizes HTML5, CSS and JavaScript (Angular) for an interactive user experience. Node.js and Spring Boot are used in the backend for handling business logic and integrations. An AI engine is deployed for predictive price analytics, Natural Language Processing (NLP) and property valuation models. For data storage, a combination of relational databases (RDS), NoSQL and cloud-based solutions are employed for both structured and unstructured data. Lastly, WebSockets is used for live auction updates and bidding transactions [1].

Frontend	HTML5, CSS, JavaScript (Angular)
Backend	Node.js, Java (Spring Boot)
AI Engine	Predictive price analytics, NLP, property valuation models
Data Storage	RDS, NoSQL, and cloud-based solutions
Real-Time Communication	WebSockets for bidding updates

Figure 2. High-Level Architecture Overview

2. LITERATURE REVIEW

The rapid advancement in artificial intelligence (AI) and machine learning (ML) has significantly transformed the real estate industry, enabling data-driven decision-making for property owners, investors, and stakeholders. Predictive analytics in real estate utilises data, statistical algorithms, and machine learning to forecast future trends and outcomes, aiding professionals in making better decisions by estimating property values, identifying investment opportunities, and predicting market fluctuations. Natural Language Processing (NLP) powers chatbots and virtual assistants that interact with customers in real-time, providing immediate assistance and information. Cloud-based architectures ensure the scalability and efficiency of AI-powered real estate platforms, enabling real-time data analytics and flexible development [9]. Furthermore, ML lifecycle management tools such as MLflow have become essential in managing the development, experimentation, and deployment of machine learning models in real estate applications. MLflow supports reproducibility and collaboration by tracking experiments, packaging code, and managing model versions across different environments[23]. By analysing these studies, this review aims to establish a strong foundation for the implementation of an intelligent, data-driven property investment and management system.

2.1 Predictive Price Analytics in Real Estate

AI-driven predictive price analytics leverage machine learning to forecast property prices based on historical transaction records, geographic location, and macroeconomic indicators. Studies have shown that AI models can provide more accurate price estimations than traditional valuation methods by considering multidimensional data points, including market sentiment and buyer behavior patterns. For instance, CBRE discusses how AI's ability to process vast amounts of data can enhance real estate market forecasting [10]. Recent advancements in deep learning and big data processing have further improved price prediction accuracy, reducing valuation errors and increasing investor confidence. A study demonstrated that the XGBoost algorithm outperforms other models in predicting house prices, highlighting the effectiveness of advanced machine learning techniques in real estate valuation [11].

2.2 AI-Driven Market Trend Analysis

Understanding market trends is crucial for property owners and investors to make informed decisions. AI-powered analytics platforms analyze real estate transaction patterns and detect shifts in property demand and pricing. These systems may utilize natural language processing (NLP) to interpret real estate news and reports, enabling users to anticipate market fluctuations and optimize their investment strategies. For example, AI can help generate market and property insights by identifying patterns and making forecasts based on vast amounts of data [12]. Cloud-based AI solutions further enhance market analysis by providing real-time data visualization and predictive insights, improving the decision-making process for real estate stakeholders. The integration of AI and machine learning in cloud architectures facilitates the development of intelligent applications that can analyze and predict market trends effectively [13].

2.3 Rental Yield Prediction Models

Accurately estimating rental yields is essential for investors to assess property profitability. AI-based rental yield prediction models integrate rental market conditions, property attributes, and economic indicators to provide more precise estimations. By incorporating real-time rental listings and transaction data, AI models can adjust predictions dynamically, ensuring investors have up-to-date insights on potential returns. Furthermore, AI-driven rental analytics help property managers optimize rental pricing strategies, maximizing occupancy rates and revenue generation. For instance, AI tools like HouseCanary use machine learning models to predict property values, market trends, and investment opportunities, aiding investors in making informed decisions [14].

2.3.1 Traditional Approaches to Rental Yield Prediction

Traditional Approaches to Rental Yield Prediction

Hedonic Regression and Econometric Models: A common traditional approach is the hedonic pricing model, which uses statistical regression to relate property attributes to rental rates and prices. By estimating separate hedonic models for rents and sale prices, one can derive an implied rental yield. For example, a study on Singapore's private housing market used a hedonic model to quantify how amenities (like MRT proximity) affect property prices. In such models, location, floor area, age, and proximity to transport are typical predictors, and coefficients are interpreted as marginal effects (e.g., moving 100m closer to an MRT station raised condo prices by ~$15k in one study). Econometric analyses are valued for interpretability – they clearly show the premium or discount associated with each factor. However, they often assume a linear (or pre-specified nonlinear) relationship and may struggle with complex interactions or nonlinear effects present in the data. Nonetheless, hedonic models remain a baseline for rental yield analysis, including in Singapore where government agencies use them to track the impact of attributes on prices and rents [15].

Time-Series Forecasting: For market-level yield trends, traditional time-series methods like ARIMA have been used. By modeling rental indices and price indices over time, one can forecast future yields (ratio of rent index to price index). For instance, Singapore's Urban Redevelopment Authority (URA) publishes quarterly indices for private home rents and prices; an ARIMA model could forecast these and hence the yield ratio. Simpler smoothing techniques or Facebook Prophet (an additive time series model) are also employed in industry for ease of use. These statistical forecasting methods can capture seasonality and general trends, but may falter when sudden policy changes or shocks occur (e.g., cooling measures or pandemics). Recent comparisons have found that while Prophet is user-friendly, advanced ML like LSTM (Long Short-Term Memory networks) often achieve lower forecast error on real estate time series [16]. In summary, traditional time-series models provide a baseline for yield trend prediction but are increasingly supplemented by ML for greater accuracy.

2.3.2 Summary of Conventional vs Modern Methods:

The table below contrasts traditional econometric and time-series approaches with modern machine learning techniques:

Approach	Examples	Strengths	Limitations
Econometric (Hedonic)	OLS regression, hedonic price model; cap-rate models	OLS regression, hedonic price model; cap-rate models	Assumes functional form; may miss complex nonlinear effects; requires expert feature selection
Time-Series (ARIMA)	ARIMA, Exponential Smoothing	Captures overall market trend and seasonality; well-understood stats methods	Needs long historical data; struggles with regime shifts (e.g. sudden demand surges)
ML Ensemble (Tree-Based)	Random Forest, XGBoost, LightGBM	Handles nonlinear interactions; often high prediction accuracy; can ingest many features	Less interpretable (feature importance can be assessed but not causal); risk of overfitting without proper tuning
ML Neural (Deep Learning)	Artificial Neural Network (ANN), LSTM RNN	Can model complex patterns; LSTM captures temporal dependencies in rental trends	Requires large data; training can be computationally intensive; "black box" model decisions

Hybrid / Ensemble	Stacking models; hybrids (e.g. PSO-optimized XGBoost)	Combines strengths of multiple models for better accuracy; can capture different aspects of data	More complex to implement and validate; interpretability further reduced

(PSO = Particle Swarm Optimization for hyperparameter tuning.)

2.3.3 Modern Machine Learning Models for Rental Yield Prediction

Recent years have seen a surge in applying machine learning to real estate prediction problems. Rather than explicitly computing yields from separate rent/price models, some approaches train models directly on rental yield (or the closely related price-to-rent ratio) [17]. More commonly, ML models predict property sale prices or rents given features, and these can be combined to estimate yield. Here we review key ML techniques:

Ensemble Tree-Based Models: Gradient-boosted decision trees and random forests have become go-to methods for tabular real estate data. These models naturally handle nonlinear relationships and feature interactions. In a study of Singapore private housing, ML models (random forest, LASSO, ANN) outperformed a hedonic regression in predicting prices [15]. Many independent projects likewise find tree ensembles excel for rental pricing. For example, an XGBoost regressor was trained on ~1,680 Singapore rental listings (features included location coordinates, distance to CBD/MRT, etc.) and achieved R^2 ~0.90 and MAPE ~13% on test data [17], substantially reducing error in rent estimates. Another project on Singapore condo rentals tested five models (Linear Regression, Random Forest, XGBoost, LightGBM, CatBoost) and noted these ensemble methods yield robust performance [18]. In a Kuala Lumpur office rental study, Random Forest achieved $R^2 \approx 0.90$, outperforming simpler models [19]. These results underscore that tree-based ML can capture the complex determinants of rent and price (and thus yield) better than linear models. A downside is interpretability, though techniques like feature importance and SHAP values help identify key drivers (e.g., one SG rental analysis found floor area, proximity to city, and MRT distance most important via Random Forest feature importance) [20].

Deep Learning Models: Neural networks have also been applied, especially for larger datasets. Feed-forward artificial neural networks (ANNs) can approximate the rent/price function given enough data. A study modeled Cape Town rentals with a neural network and found floor area to be the top predictor, with the model correctly classifying rent ranges ~66% of the time. In practice, simpler tree models often rival ANNs on structured data; however, LSTM networks shine in time-series forecasting. An LSTM can learn temporal patterns in rental indices or in sequences of quarterly yields. Studies comparing LSTM to ARIMA/Prophet for housing rents show LSTMs can achieve higher accuracy, e.g., one analysis found an LSTM gave <10% deviation in day-ahead forecasts, outperforming Prophet and random forest on temporal metrics. To leverage both structured and temporal aspects, hybrid architectures are proposed: one could use gradient boosting on cross-sectional features (location, size, etc.) combined with an LSTM for capturing market trends. Indeed, hybrid models are a trend in recent literature – for example, researchers have combined Facebook Prophet with LSTM to create ensemble forecasts that handle both seasonality and complex patterns [16].

Hybrid and Advanced Ensemble Methods: Beyond single models, stacking or blending multiple models can improve predictive performance. A study developed a stacked ensemble (GBDT, XGBoost, and a neural network, stacked with XGBoost as meta-learner) for housing price prediction and found it outperformed any individual model [16]. Another innovative approach is optimizing models with meta-heuristics: a study combined Particle Swarm Optimization (PSO) with XGBoost to tune parameters and reported it captured nonlinear relationships better, yielding higher accuracy than non-hybrid models. Such hybrid models could be applied to rental yield by training on large transaction datasets – for example, one model might predict rent, another price, and a meta-model learns to adjust or directly predict yield. While ensembles improve accuracy, they also highlight a gap: most ML approaches predict either rent or price, not yield directly. An opportunity for future work is to develop models that directly output rental yield (perhaps via multi-task learning that predicts rent and price together to ensure consistency) [21].

2.4 Demand Forecasting for Real Estate

Demand forecasting plays a critical role in balancing property supply with market demand. AI models trained on historical housing data, demographic trends, and economic conditions can predict future housing demand over different time frames. This capability allows property developers and policymakers to make proactive decisions regarding housing supply, urban planning, and investment allocations. The use of AI in demand forecasting also supports dynamic pricing strategies, enabling property owners to adjust rental or sale prices based on projected market trends. Predictive analytics in real estate uses data, statistical algorithms, and machine learning to forecast future trends and outcomes, aiding professionals in making better decisions [6].

While the literature often suggests using hybrid or ensemble approaches to overcome the limitations of single models, this study focuses on evaluating each model individually to determine the best performer for real estate demand forecasting. By conducting a standalone analysis of each model, the study aims to provide clear insights into the comparative strengths and weaknesses of ARIMA, LSTM, and XGBoost. This independent evaluation approach is crucial for identifying the most reliable and accurate forecasting method before considering any model integration or ensemble strategies [22].

2.5 AI and NLP in Real Estate Transactions

Natural Language Processing (NLP) has been increasingly applied to real estate platforms to enhance customer interactions and automate decision-making processes. AI-driven chatbots, text summarization techniques, and sentiment analysis models have improved customer engagement by offering personalized recommendations and automating responses to property inquiries. For example, AI chatbots can handle initial inquiries, facilitate scheduling, and provide market information, thereby enhancing customer service in the real estate sector [24]. Research also highlights how NLP can be used to extract key information from lease agreements, policy documents, and market reports, streamlining administrative processes and reducing manual workloads. Enhanced with AI-based NLP capabilities and superior context understanding, bots in real estate can replace or assist managers in performing a wide range of clerical tasks [25].

2.6 Cloud-Based Architectures for AI-Driven Platforms

Modern real estate platforms leverage cloud computing for scalable and efficient data processing. Studies on cloud-based architectures emphasize the use of microservices, containerization, and serverless computing to deploy AI-driven applications. Research has demonstrated that cloud-based AI solutions provide enhanced flexibility, lower operational costs, and real-time data analytics capabilities. For instance, integrating AI and machine learning in the cloud establishes the architectural foundations for intelligent applications, enabling real estate platforms to process large datasets efficiently and deliver insights in real-time [26].

3. PROBLEM STATEMENT

The lack of AI-driven predictive analytics and data-driven decision-making tools in Singapore's real estate market makes it challenging for property stakeholders to navigate fluctuating prices, evolving government regulations, and shifting market trends efficiently.

Singapore's real estate market is constantly evolving, shaped by economic trends, government regulations, demographic changes, and buyer behavior. In recent years, public housing resale prices have surged by 9.6% in 2024, mainly due to strong demand and limited supply [27]. This has led to growing concerns about housing affordability, making it increasingly difficult for buyers to secure suitable properties within their budget.

To manage market stability, the government has implemented cooling measures such as lowering loan limits for property buyers [28]. While these interventions aim to prevent speculative price hikes, they also create new challenges for property investors and developers, who must navigate an increasingly complex landscape with limited financial flexibility. As a result, there is a growing need for advanced tools that can help stakeholders make data-driven decisions in this fast-changing environment.

Artificial Intelligence (AI) has emerged as a powerful solution to these challenges. AI-driven platforms are transforming Singapore’s real estate sector by enabling automated property recommendations, predictive analytics, and enhanced user experiences. For instance, property search portals like Mogul.sg leverage AI to match buyers with suitable properties based on their preferences and budget [29]. Additionally, AI is being adopted in commercial real estate to improve operational efficiency, optimize property pricing, and provide real-time market insights [30].

However, despite these technological advancements, the integration of AI in real estate still faces several obstacles. One major challenge is the need for comprehensive and high-quality data. AI models rely on vast amounts of historical transactions, rental trends, and economic indicators, but data access and privacy regulations can limit the effectiveness of predictive analytics [31]. Additionally, implementing AI solutions requires significant investment in infrastructure, training, and expertise, which may pose barriers for smaller property firms and independent investors [33].

Additionally, implementing AI solutions requires significant investment in infrastructure, training, and expertise, which may pose barriers for smaller property firms and independent investors [31]. While AI adoption has increased among larger agencies, many traditional real estate businesses still struggle to integrate AI-driven analytics into their workflows [34].

Moreover, as AI technologies continue to advance, real estate professionals must adapt to new tools and methodologies. The rapid pace of innovation means that property stakeholders must continuously update their knowledge to fully utilize AI-driven insights for better decision-making [32]. Without proper adoption and integration, the full potential of AI in real estate may remain underutilized.

4. POTENTIAL PROPOSED SOLUTION

To address the complexities of property valuation, market forecasting, and rental analysis in the Singapore real estate market, this project adopts advanced machine learning and statistical models to build robust and intelligent prediction systems. These solutions aim to overcome the limitations of traditional methods by capturing complex, nonlinear relationships in large datasets. The platform leverages ensemble learning models like XGBoost, temporal models such as Long Short-Term Memory (LSTM) networks, and statistical models like Autoregressive Integrated Moving Average (ARIMA) to explore different approaches for price forecasting.

Each of these models is applied to the dataset and evaluated using appropriate performance metrics, which are further explained below in section 5. By benchmarking the models against each other, the system identifies the most suitable model for each predictive use case. XGBoost is evaluated for its ability to handle structured data with multiple input features, LSTM for its capability to capture long-term dependencies in time series data, and ARIMA for its effectiveness in univariate time series forecasting. This comparative analysis ensures that the final model selection is based on empirical performance, optimizing accuracy and generalization for real-world applications.

In order to support scalable deployment and real-time performance, the solution will be containerized using Docker and deployed on Amazon Web Services (AWS). The system architecture leverages services such as Amazon ECS for storing Docker images, and Amazon S3 for secure dataset and artifact storage. MLflow is integrated on ECS to manage model versioning and performance tracking. Additional services like AWS Lambda and API Gateway are used to enable dynamic inference capabilities through RESTful APIs, while Amazon CloudWatch ensures system monitoring, fault detection, and logging. This cloud-native deployment approach provides flexibility, cost-efficiency, and high availability for production-ready AI model deployment in the real estate analytics platform.

Architecture Portion	**Service Name**	**Description**
Data Ingestion and Storage	Amazon S3 (Batch Data Storage)	Stores CSV datasets for model training
	AWS EventBridge (Triggering ML Pipeline)	Triggers the ML pipeline when new data arrives
Model Training and Deployment	AWS Step Functions	Automates and manages the ML training process
	Amazon ECS (Batch-enabled)	Runs training jobs using containerized models
	Amazon ECR	Stores the trained model in a container
API and Real-Time Predictions	AWS Lambda (Auto Scaling enabled)	Runs model predictions when needed
	AWS API Gateway	Provides an API for users to get predictions
Monitoring and Security	Amazon Cloudwatch	Monitors logs, failures and system performance
	AWS IAM	Manages access control and security policies
	MLflow (hosted on ECS)	Keeps track of model versions and performance

Figure 3. Suggested ML Pipeline with AWS Services

4.1 XGBOOST (Extreme Gradient Boosting)

XGBoost is an advanced machine learning algorithm that builds multiple decision trees sequentially, where each new tree corrects the errors of the previous trees. It uses gradient boosting to minimize prediction errors and includes regularization to prevent overfitting[35]. XGBoost handles missing values, sparse data, and high-dimensional datasets efficiently. It is widely used for structured data and delivers fast, accurate predictions [36].

4.2 Long Short Term Memory (LSTM)

LSTM is a type of neural network designed to handle sequential data and long-term dependencies. It overcomes the limitations of traditional Recurrent Neural Networks (RNNs) by using memory cells and gates that control the flow of information. LSTM is highly effective for time series forecasting and can capture complex patterns over long time periods. However, it requires a large amount of training data and is computationally intensive.modeling where long-term context is important, such as real estate market trend analysis and rental demand forecasting, due to their ability to remember information over long sequences without losing relevant signals [37].

4.3 ARIMA (Autoregressive Integrated Moving Average)

ARIMA is a statistical model used for time series forecasting that relies on past observations to predict future values. It consists of three key components [38]:

- **Autoregression (AR):** Uses past values to predict the present.
- **Integration (I):** Makes the data stationary by differencing.
- **Moving Average (MA):** Accounts for past errors to improve accuracy. ARIMA is suitable for univariate time series data and is effective when the primary information is contained within the historical values.

4.4 Methodology for tracking performance

MLflow is used to manage the lifecycle of each model. During training, the system logs each model's parameters, performance metrics, and the model itself as an artifact. This ensures experiment reproducibility and enables users to track which configuration yields the best results. Input examples are also logged to help with later inference or deployment.

5. CURRENT WORK

The current phase of the project focuses on the development and integration of machine learning models to support data-driven property investment decisions. The team is actively building and training predictive models on each of the sections within predictive analytics, namely property price forecasting, market trend analysis, rental yield prediction and demand forecasting, using historical HDB transaction data. MLflow has been integrated into the workflow for efficient experiment tracking and model versioning, enabling better model management and performance comparison. This stage aims to evaluate model accuracy using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are defined as follows:

MAE: Represents the average error between actual and predicted values in raw terms. For example, an MAE of 10,000 means the predicted price is off by approximately $10,000.

RMSE: Similar to MAE but gives more weight to larger errors, making it useful for identifying significant deviations.

MAPE: Expresses the error as a percentage of the actual value. For instance, a MAPE of 5% means the predicted price is, on average, 5% away from the actual value.

The dataset used in the current work is the publicly available resale flat prices dataset from Data.gov.sg, which includes historical records of HDB transactions in Singapore from 1990 onwards [39]. This dataset contains detailed information such as town, street name, flat type, floor area, storey range, flat model, remaining lease, transaction month, and resale price. It serves as a reliable source for analyzing long-term market trends, evaluating model performance and building machine learning models to forecast future resale prices based on engineering features and temporal patterns.

Github Repository Link: https://github.com/Rianna2002/ITPG1WizVision

5.1 Property Price Forecasting

5.1.1 Objective of Property Price Forecasting

The primary goal of this is to develop a predictive model that allows homeowners to estimate the resale value of their HDB flats based on key property details. Users will be able to input features such as **town, floor number, square feet, flat model, and flat type** to receive an accurate price estimate. This tool aims to provide homeowners with a better understanding of their property's market value, empowering them to make more informed decisions regarding resale or upgrades.

5.1.2 Model Comparisons

Note: For ARIMA, only Sengkang 5-Room sales were used due to the nature of ARIMA.

Model	**MAE**	**RMSE**	**MAPE**
LSTM	70257.19	113123.99	11.67%
XGBOOST	45508.49	64478.84	7.16%
ARIMA	31572.31	36421.00	4.72%

Figure 4. Model Comparison Table for Property Price Forecasting

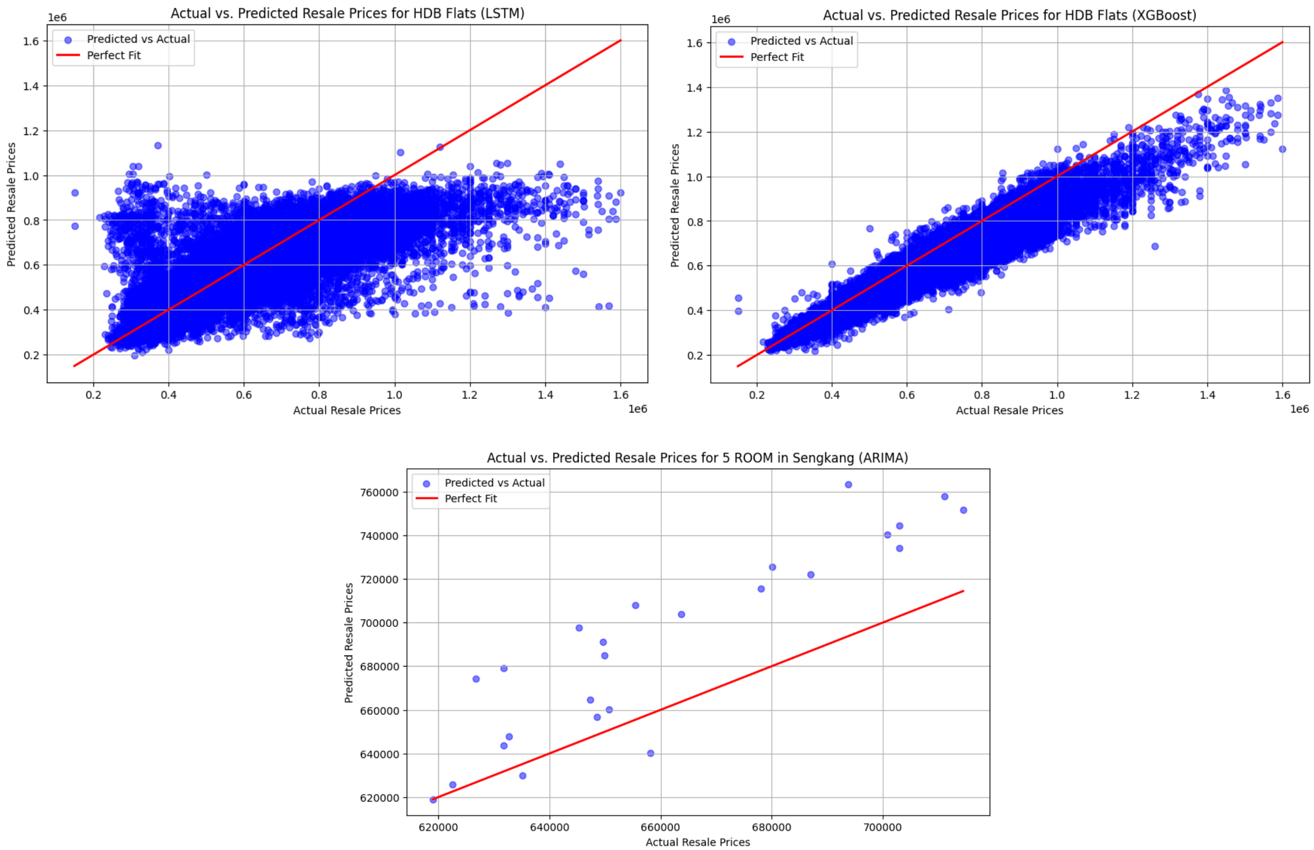

Figure 5 Model Comparison for Actual vs Predicted Sales

5.1.3 Proposed Model

XGBoost has been selected as the proposed model due to its ability to handle multiple user-input features effectively, such as flat type, floor range, and other relevant factors. It is also capable of scaling efficiently with large datasets, making it more adaptable to real-world implementation.

Although ARIMA achieved the lowest MAPE (4.72%), indicating higher predictive accuracy in percentage terms, it is not the most practical model for deployment. ARIMA predictions were limited to Sengkang 5-Room flats due to the nature of the model, which works best with time series data and fewer feature inputs. To incorporate multiple user-input features with ARIMA, a separate model would need to be trained for each unique combination of inputs, drastically reducing the dataset size for each subset and making the approach infeasible.

In contrast, XGBoost, despite having a slightly higher MAPE (7.16%), generalises better and allows for the inclusion of a wider range of user inputs, making it the more suitable choice for the task.

5.1.4 Implementation of XGBoost for Property Price Forecasting.

The dataset underwent several preprocessing steps to ensure it was ready for modeling. First, a custom order was defined for categorical features such as town, flat_type, storey_range, and flat_model to maintain consistency during encoding. Next, one-hot encoding was applied to the town and flat_model columns, while flat_type and storey_range were label-encoded based on the predefined order.

Following this, feature engineering was performed by converting the month column to datetime format and extracting the year and month as separate features (year and month_num), which provided additional time-based information for the model. After cleaning and transforming the data, the target variable (resale_price) was defined, and the dataset was split into training and testing sets using an 80/20 split to ensure a balanced evaluation of model performance.

5.2 Market Trend Analysis

5.2.1 Purpose and Goals of Forecasting HDB Resale Trends

The objective of this market trend analysis is to uncover patterns in HDB resale prices over time and predict future price movements using data-driven models. By analyzing historical transaction data, including factors such as location, flat type, floor area and lease details, this study aims to support better decision-making for buyers, sellers and policymakers. The ultimate goal is to identify the most effective predictive model that can provide accurate, timely insights into Singapore’s housing market trends, enabling more informed planning and investment strategies.

5.2.2 Data Preparation and Feature Engineering

The application processes five datasets from the HDB resale flat price records (1990 to 2024), consolidating them into a single dataframe. Temporal features such as year, month, and quarter are extracted from the transaction month. Categorical features like town, street name, flat type, storey range, and flat model are encoded using label encoding. The remaining lease column is cleaned and converted to numerical format for model compatibility.

5.2.3 Predictive Modelling and Model Comparison

To forecast HDB resale flat prices, three different predictive models were developed and compared: XGBoost, LSTM, and ARIMA. These models were trained on the same pre-processed dataset, which includes relevant features such as town, street name, flat type, storey range, flat model, floor area, remaining lease, and transaction dates (year and month).

To ensure a fair comparison, all models used the same train-test split ratio (80/20). Model performance was evaluated using three common regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Model	**MAE**	**RMSE**	**MAPE**
XGBoost	13241.14	19265.25	4.76%
LSTM	16454.58	18599.16	3.07%
ARIMA	69533.19	19361.81	12.59%

Figure 6. Model Comparison Table for Market Trend Analysis

5.2.4 *Proposed Model for Market Trend Analysis*

As shown in Figure 4, the XGBoost model achieved the lowest MAE, indicating the smallest average prediction error. It also performed competitively in RMSE, suggesting it handles large errors well. Although LSTM had a slightly lower RMSE than XGBoost, it had a higher MAE, implying more frequent moderate errors. Notably, LSTM achieved the lowest MAPE, indicating better proportional accuracy across different price ranges. In contrast, ARIMA performed the worst across all three metrics, with the highest MAE and MAPE, suggesting it struggles to capture the complexity of resale price patterns in the dataset.

Overall, XGBoost remains the most consistent and reliable model, achieving strong results across all metrics and offering a good balance between absolute accuracy and percentage-based performance. LSTM is a competitive alternative, especially when proportional accuracy is more important. ARIMA, however, is less suitable for this task due to its limited ability to model non-linear and feature-rich data.

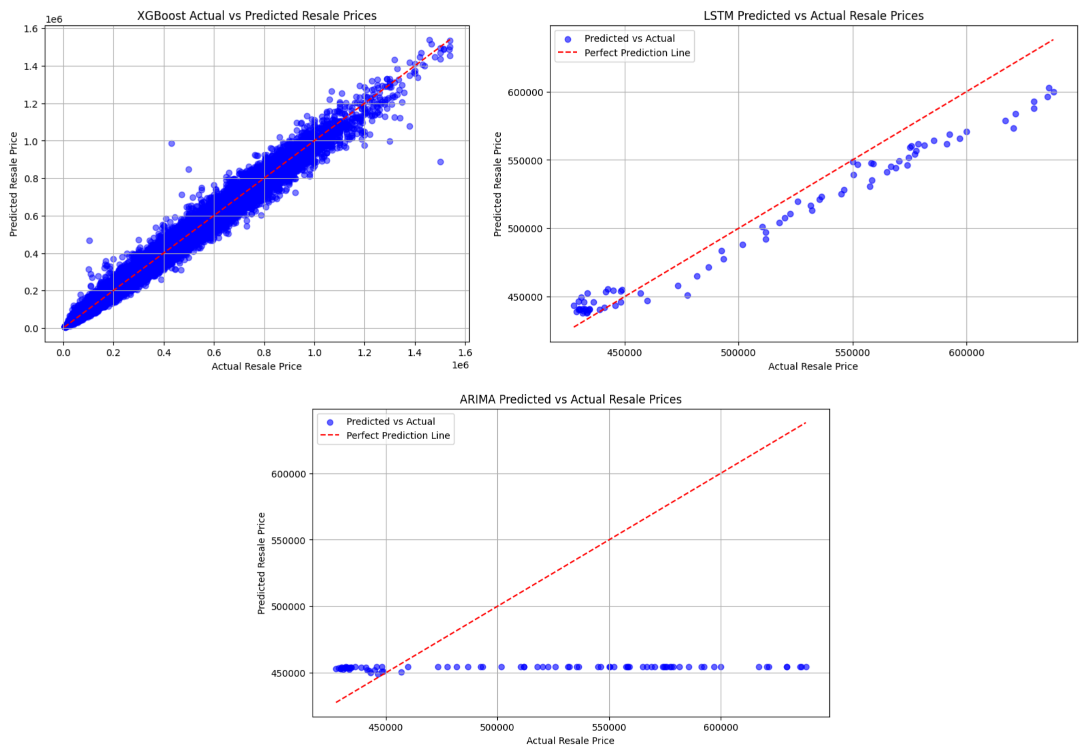

Figure 7. Model Comparison for Actual vs. Predicted Resale Prices

5.2.5 *Market Trend Visualisation*

Beyond model comparison, the app includes interactive data visualisations to support market trend analysis. Users can view average resale price trends over time and identify price patterns across decades. The system highlights the top 10 most expensive towns overall and the top 5 per decade, providing insights into how location-based pricing has evolved.

5.2.5.1 *Resale Price Trends*

Average resale prices are tracked over the years to observe market growth or decline. As seen in Figure 6, resale prices have shown a general upward trend from 1990 to 2025, with a few periods of stagnation or slight dips. This long-term growth indicates strong market demand and appreciation in public housing value overtime. Significant increases are observed around the late 2000s and post-2020, possibly driven by policy shifts, supply-demand imbalance, or economic factors like low interest rates.

Understanding these patterns enables better forecasting and strategic planning for both buyers and policymakers. For instance, a steady rise in prices post-2019 may highlight the impact of changing demographics or evolving house needs, making it crucial to adapt development plans accordingly.

Figure 8. Resale Price Trends Over Time

5.2.5.2 Price Distribution Across Towns

Identifying price variations across towns helps pinpoint high-demand areas and investment opportunities. As illustrated in Figure 7, towns like Punggol, Bukit Timah, and Sengkang consistently command higher average resale prices, reflecting their popularity among buyers. These areas may offer better amenities, newer developments, or strategic locations near key transport and commercial hubs.

This analysis is useful for real estate investors and planners to detect pricing clusters and prioritize resource allocation. It also informs prospective homeowners about affordability gaps between regions. For example, towns with lower average resale prices such as Marine Parade or Central Area may be less in demand or have older flats, influencing renovation or redevelopment strategies.

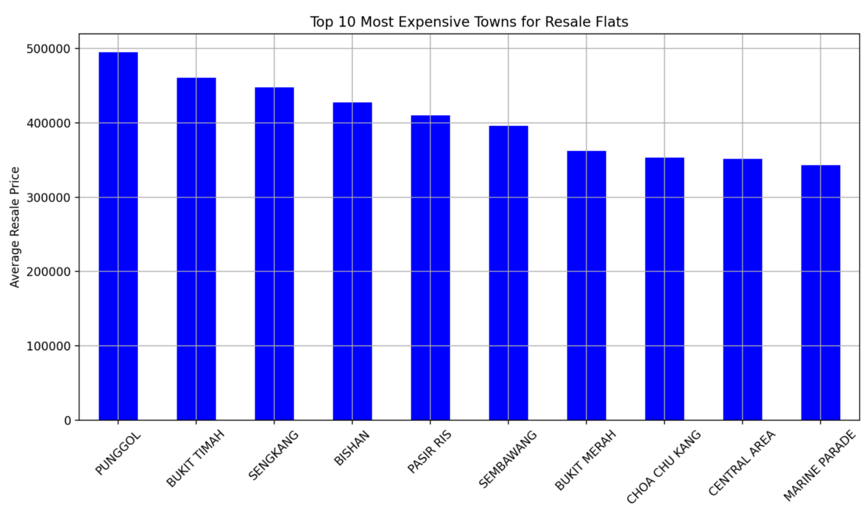

Figure 9. Top 10 Most Expensive Towns for Resale Flats

5.3 Rental Yield Prediction

5.3.1 Overview of Implementation

The system implements a comprehensive approach to rental prediction that forms the foundation for rental yield calculations. The codebase establishes a robust pipeline for preprocessing rental data, training multiple predictive models, and deploying these models through an interactive web application.

5.3.2 Data Processing Framework

The DataProcessor class provides essential functionality for preparing Singapore rental data:

Automated handling of date columns, extracting temporal features

Categorical variable encoding using one-hot encoding

Numerical feature standardisation

Efficient train-test splitting for model evaluation

This preprocessing framework ensures that all relevant property features are appropriately formatted for the machine learning models, which is crucial for accurate rental predictions that would subsequently feed into yield calculations.

5.3.3 Model Architecture

The system employs multiple modelling approaches to maximise prediction accuracy:

XGBoost: A gradient boosting framework that handles complex feature relationships

LSTM: A deep learning approach capturing temporal dependencies in the data

ARIMA: A traditional time-series model providing baseline predictions

All models are trained to predict the monthly_rent variable, which serves as the primary component for rental yield computations.

5.3.4 Performance Evaluation

The comparative model performance is thoroughly analysed through multiple metrics:

RMSE (Root Mean Squared Error): LSTM and XGBoost demonstrate significantly lower error rates (approximately 500) compared to ARIMA (approximately 700), indicating better prediction accuracy.

MAE (Mean Absolute Error): Similar pattern with LSTM showing the lowest error at around 370, compared to ARIMA's 610.

MAPE (Mean Absolute Percentage Error): LSTM achieves the lowest percentage error at 15%, while ARIMA shows higher error rates at approximately 25%.

Figure 10. Loss Metrics comparison of the 3 models

Model	MAE (S$)	RMSE (S$)	MAPE (%)
ARIMA	610	700	25.0
LSTM	370	500	15.0
XGBoost	380	500	15.5

Figure 11.Table comparison

These metrics suggest that the LSTM model provides the most reliable rental predictions, which would translate to more accurate yield calculations.

5.3.5 Advantages of XGBoost Implementation

XGBoost offers substantial benefits from a resource utilisation perspective. Unlike LSTM models which require significant computational resources for training and inference, XGBoost operates efficiently on standard hardware configurations. This translates to:

- Lower infrastructure costs for both development and deployment
- Faster training cycles enabling more frequent model updates
- Reduced inference latency for real-time prediction scenarios
- Simpler deployment architecture without specialised GPU requirements

5.3.6 Performance Considerations

The performance metrics support this pragmatic approach. XGBoost demonstrates nearly identical prediction accuracy to LSTM:

- RMSE values are equivalent (500 for both models)
- MAE shows only a 10-point difference (380 vs 370)
- MAPE reflects a negligible 0.5% difference (15.5% vs 15.0%)

This minimal performance differential does not justify the substantially higher resource requirements of the LSTM approach, particularly in a production environment where operational efficiency is paramount.

5.3.7 Implementation Recommendation

I recommend proceeding with XGBoost as the primary model for rental yield prediction. The implementation should include:

- A regular retraining schedule to maintain model currency with market conditions
- Comprehensive feature engineering to maximise the model's predictive capabilities
- A lightweight deployment configuration suitable for scalable web service implementation
- Continued monitoring of performance metrics against the LSTM benchmark

This balanced approach will deliver optimal prediction accuracy while maintaining reasonable hardware requirements and operational simplicity for the rental yield prediction system.

5.4 Demand Forecasting

5.4.1 Objective of Property Price Forecasting

The primary objective of demand forecasting is to accurately predict the number of property transactions for each month, helping stakeholders make informed decisions about housing supply, pricing strategies, and urban planning. By leveraging historical transaction data and advanced machine learning techniques, the platform aims to forecast demand fluctuations in the real estate market, thereby supporting optimal resource allocation and investment planning.

5.4.2 Data Preparation and Feature Engineering

The dataset used for this analysis contains historical transaction records for HDB properties. Initially, the dataset is loaded and preprocessed for model compatibility. Key preprocessing steps include:

- Converting the 'month' column into a proper datetime format to enable time-series analysis.\
- Aggregating data by 'month' and 'town' to count the number of transactions, creating the target variable 'transaction_count'. This preprocessing resulted in an aggregated dataset which captures monthly transaction volumes, which is crucial for accurate time-based forecasting.

The feature engineering process is as follows:

- Lag Features: To capture temporal patterns, lagged variables were created for the XGBoost model. This helps the model account for temporal dependencies.
- Sliding Window Technique: This technique was used to generate rolling statistics and capture trends over time for the LSTM model.
- Normalization: Data was normalized to maintain uniformity, especially since models like LSTM and XGBoost can be sensitive to scale differences.
- Train-Test Split: The dataset was divided into training and testing subsets to evaluate model performance without data leakage.

By employing these data preparation and feature engineering techniques, the models were able to leverage both historical patterns and temporal relationships effectively, thereby improving the accuracy of demand forecasting.

5.4.3 Model Comparisons

To accurately predict property transaction counts, three models were implemented and compared as shown in Figure 10 below.

Model	MAE	RMSE	MAPE
LSTM	28.27	339.85	104.59%
XGBOOST	22.47	33.99	37.97%
ARIMA	884.30	894.34	43.66%

Figure 12. Model Comparison Table for Demand Forecasting

The XGBoost model outperformed both LSTM and ARIMA, achieving the lowest RMSE and MAE, indicating superior accuracy and robustness. The LSTM model, while capable of capturing temporal patterns, exhibited higher error rates, likely due to noise sensitivity and insufficient data to train a deep learning model effectively. ARIMA, despite being a traditional statistical approach, performed poorly, struggling to handle nonlinear patterns and temporal complexities inherent in real estate data.

5.4.4 Proposed Model

Given the superior performance metrics, XGBoost was selected as the optimal model for demand forecasting. It offers a balance between accuracy and computational efficiency, making it suitable for real-time applications in property transaction prediction. The model's ability to handle structured data and nonlinear relationships makes it a reliable choice for forecasting complex market dynamics.

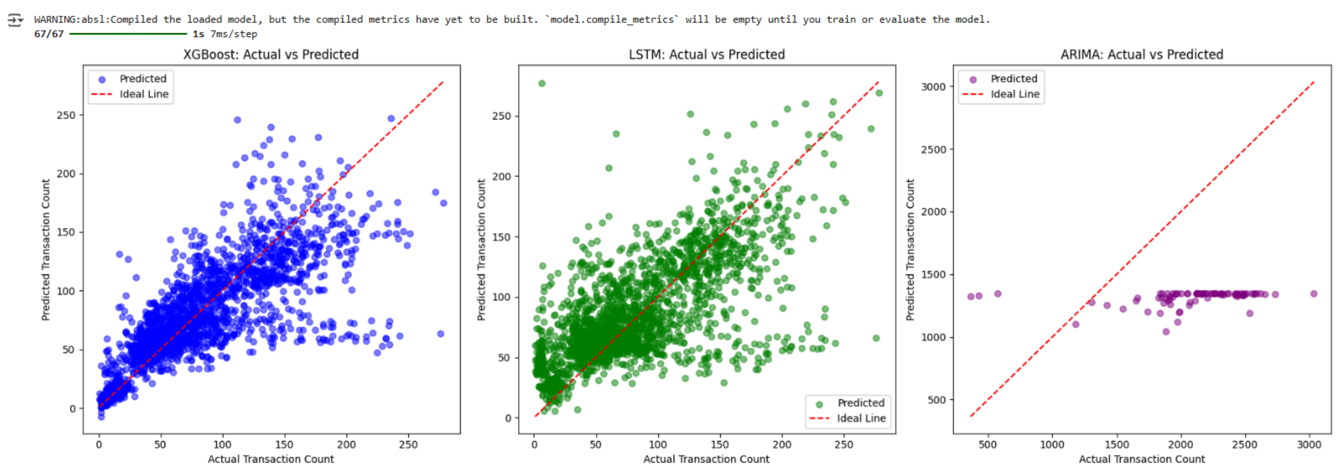

Figure 13. Model Comparison Table for Actual vs Predicted Transaction Count

Additionally, figure 11 presents the Actual vs Predicted Transaction Counts for three demand forecasting models: XGBoost, LSTM, and ARIMA. The graph visually demonstrates how each model's predictions align with the actual transaction data, with the ideal line (red dashed line) representing perfect predictions.

Among the three models, XGBoost clearly outperforms the others, as evidenced by its predicted values (blue dots) being closely clustered around the ideal line. This tight alignment indicates that XGBoost captures both linear and nonlinear patterns in the data effectively, resulting in highly accurate and consistent predictions. The reduced variance in predictions further highlights its reliability, even when dealing with higher transaction counts.

Overall, the XGBoost model emerged as the best-performing model with the lowest MAPE, RMSE, and MAE, significantly outperforming both the LSTM and ARIMA models.

6. CONCLUSION

The AI-enabled Asset Owner Platform project seeks to transform data-informed decision-making in Singapore's property sector. The platform combines predictive analytics with cloud infrastructure to project property prices, rental returns, market trends, and housing demand. By employing historical HDB resale data dating back to 1990, the project assesses three machine learning models—XGBoost, Long Short-Term Memory (LSTM), and ARIMA—analyzing their performance through Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). XGBoost proved to be the most reliable model, successfully maintaining a balance between performance and efficiency, while LSTM showed excellent temporal pattern recognition, and ARIMA acted as a dependable benchmark for univariate forecasting.

The platform's implementation utilizes Amazon Web Services (AWS) for scalability and immediate analysis, incorporating MLflow for tracking models and visualization tools for market insights. Through effective data handling and feature development, the system guarantees precise and flexible forecasts, allowing stakeholders to make educated investment choices and enhance property management tactics. The initiative also anticipates additional improvements via real-time data integration, sophisticated model frameworks, and scalable cloud optimization to stay pertinent in the evolving real estate market.

7. PROSPECTS

The Asset Owner Platform with AI project presents numerous opportunities for future development and enhancement. As the real estate market continues to evolve and technological advancements progress, the platform can integrate more sophisticated features and expand its application areas.

7.1 Gantt Chart for ITP1 and ITP2

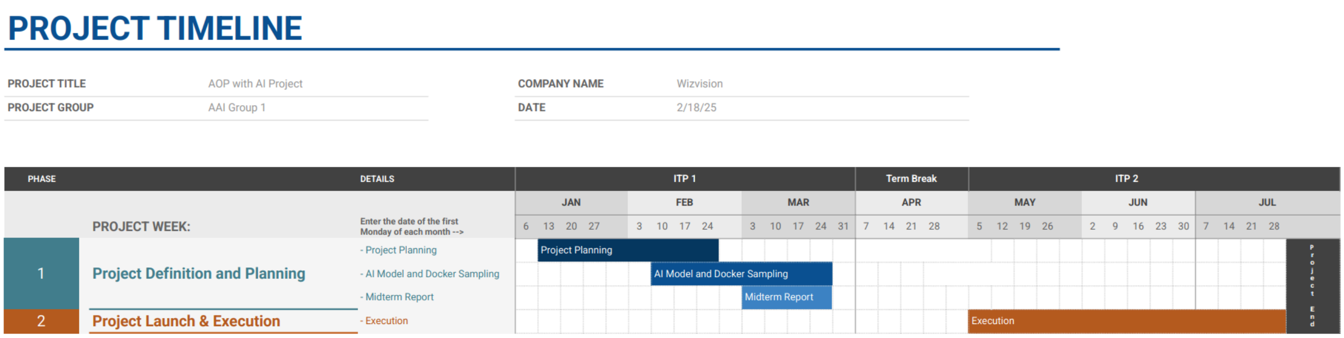

Figure 14. Project Timeline for AOP with AI Project

As shown in Figure 14, while the work done in ITP1 catered towards project definition and planning, further developments will be made on the project during ITP2.

7.2 Future Enhancements

Several potential enhancements can be implemented to increase the system's efficiency and user engagement:

1. **Integration of Real-Time Data Sources:**
    - Integrating real-time data streams from government housing databases and property listing platforms can further enhance the model's accuracy and relevance.
    - Incorporating live data updates through APIs will allow the platform to provide up-to-date property valuations and market trend analyses.
2. **Advanced Predictive Modeling Techniques:**
    - To improve the accuracy of demand forecasting, experimenting with more advanced models like Transformer-based architectures and hybrid models (e.g., combining LSTM with XGBoost) could be valuable.
    - Implementing deep learning approaches for property image analysis could assist in better valuation predictions.
3. **Scalability and Cloud Optimization:**
    - Optimizing the existing architecture to leverage serverless computing through AWS Lambda functions can reduce operational costs while maintaining performance.
    - Exploring other cloud providers such as Google Cloud Platform (GCP) or Microsoft Azure for multi-cloud deployment could improve system resilience and availability.

7.3 Expansion of Use Cases

The current focus on property price forecasting and rental yield prediction can be expanded to address additional scenarios, including:

- **Property Investment Risk Assessment:**
    - Developing risk models that evaluate market volatility and economic risks associated with property investments.
- **Smart Contract Integration:**
    - Leveraging blockchain technology to automate contract generation and record property transactions securely.
- **Integration with IoT and Smart Devices:**
    - Connecting with smart home systems to track property conditions and maintenance requirements.

7.4 Long-Term Vision

The long-term goal is to position the Asset Owner Platform as a comprehensive real estate intelligence hub that supports not only property owners but also real estate developers, investors, and government bodies. By continuously integrating cutting-edge AI models and maintaining an adaptive system architecture, the platform can remain competitive and relevant in the fast-paced real estate market.

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