Journal of Theoretical and Applied Information Technology
31st October 2024. Vol.102. No. 20

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IMPROVING DEMAND FORECASTING ACCURACY WITH MACHINE LEARNING MODELS: CASE STUDY OF AN INDONESIAN FMCG COMPANY

FRIZA ARMEN[1], RIYANTO JAYADI[2]

[1]*BINUS Graduate Program – Master of Information System Management, Bina Nusantara University, Jakarta, Indonesia*

[2]*BINUS Graduate Program – Master of Information System Management, Bina Nusantara University, Jakarta, Indonesia*

E-mail: [1]friza.armen@binus.ac.id, [2]riyanto.jayadi@binus.edu

ABSTRACT

The FMCG industry in Indonesia is experiencing rapid growth but faces challenges in accurate demand forecasting. This can lead to operational inefficiencies and unnecessary costs. This study aims to improve demand forecasting accuracy by applying various machine learning models and identifying the best model for specific product categories. The study uses historical sales data from an FMCG company in Indonesia to evaluate the performance of seven machine learning models: Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), ARIMA, Linear Regression (LR), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM). The results indicate that the Exponential Moving Average (EMA) model consistently outperforms others across all product categories. Specifically, EMA achieves MAPE values as low as 0.22% in Instant Food and 0.24% in Beverages. This study recommends that FMCG companies in Indonesia use Exponential Moving Averages to improve demand forecasting accuracy. Additionally, the study contributes valuable insights to industry knowledge by providing new perspectives on effective forecasting techniques.

Keywords: *FMCG, demand forecasting, machine learning, Exponential Moving Average, Indonesia*

1. INTRODUCTION

The FMCG (Fast Moving Consumer Good) industry in Indonesia plays a central role in the national economy. This industry is experiencing rapid growth, with a growth of 5.33% in the first three months of 2023. Food and beverage products contribute the largest share of 38.61% of the gross domestic product (GDP) of Indonesia's non-oil and gas processing industry in the first quarter of 2023.

Despite the rapid growth, the FMCG industry often faces challenges in accurate demand forecasting. One of the problems facing this industry is that it is highly susceptible to the bullwhip effect, which is influenced by dynamic market movements. Market fluctuations, changes in consumer trends, promotions that affect demand dynamics [1] and other external factors often affect forecasting, which in turn can lead to problems such as excess inventory that burdens storage costs or stockouts. Therefore, improving demand forecasting accuracy has significant significance in helping FMCG companies [2].

In addition to the challenges mentioned above, FMCG companies in Indonesia also face difficulties in accurately calculating Daily Inventory Outstanding (DIO). DIO is a key metric that measures the average amount of inventory held each day. Accurate DIO calculation is essential for optimizing inventory levels and minimizing costs. The formula for calculating DIO is **DIO =Inventory/ (Cost of Goods Sold (COGS)) x 365**. In this formula, Inventory represents the total value of goods held by the company during the reporting period, while Cost of Goods Sold (COGS) denotes the direct costs attributable to the production of goods sold within the same period. The constant 365 is used to convert the inventory turnover ratio into days.

This benchmark [3], as illustrated in Figure 2, provides FMCG companies with a valuable

Journal of Theoretical and Applied Information Technology
31st October 2024. Vol.102. No. 20

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

reference point for assessing their inventory performance and identifying areas for improvement. By comparing their DIO levels to the industry benchmark, FMCG companies, which have an average DIO of 72 days, can gain insights into their inventory efficiency, and make informed decisions to optimize their supply chains.

To address the challenges, a study was conducted on an FMCG company in Indonesia. In 2022, the company's COGS (Cost of Goods Sold) amounted to Rp. 19,34 T and its inventory value was Rp. 3,87 T. These figures indicate that the company's DIO (Daily Inventory Outstanding) was at **73 days**, one day above the FMCG industry average according to Deloitte, and equivalent to holding excess stock worth Rp. 52,9 M Additionally, the trend of demand forecasting accuracy in 2022, as measured by MAPE (Mean Absolute Percentage Error), for the FMCG company is shown in the graph below:

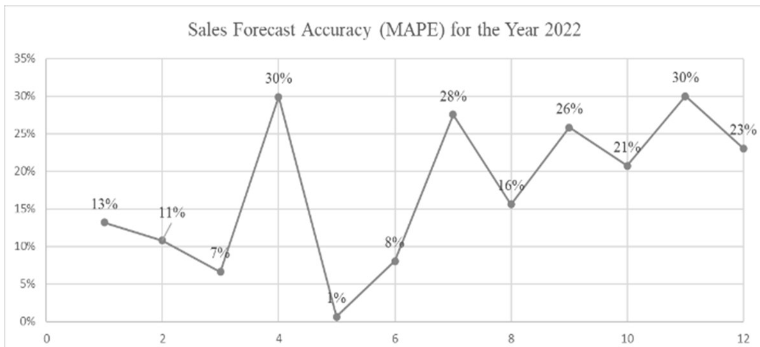

Figure 1: Sales Forecast Accuracy Year 2022

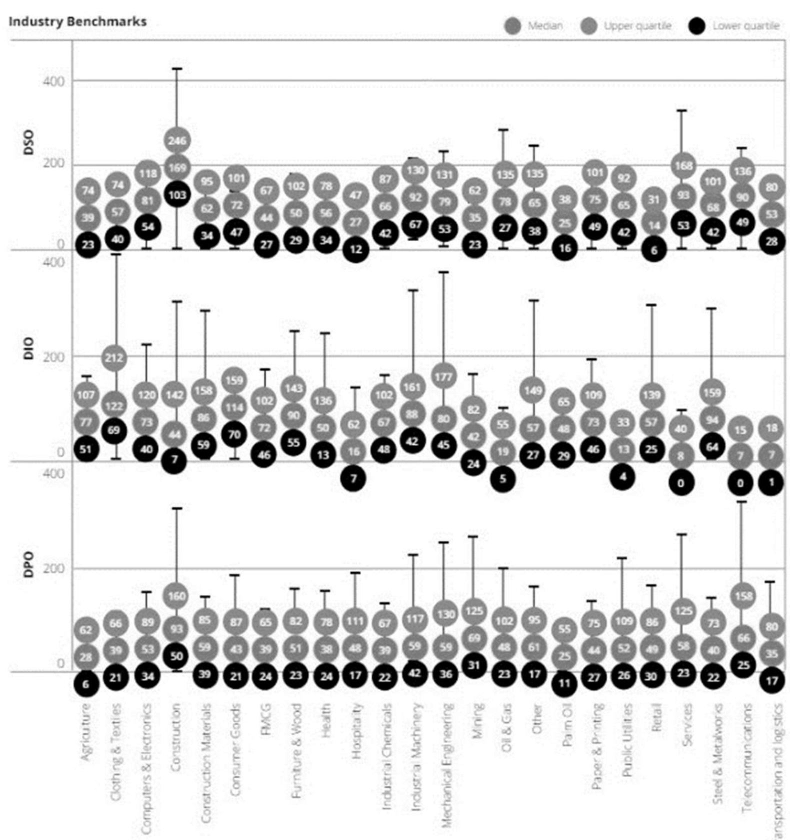

Figure 2: Industry Benchmark

The benefits of this research are very relevant and substantial, including improving forecasting accuracy which can help FMCG companies avoid uncertainty and optimize supply chains. This also has an impact on operational efficiency by reducing unnecessary costs. This improved forecasting accuracy will also allow companies to better meet customer demand, increase customer satisfaction, and better face competition. Provide valuable contributions to industry knowledge by providing new insights into effective forecasting techniques. Encourage the development of human resource capabilities in mastering machine learning technology and relevant data analysis. Have an impact on the national economy through contributions to economic growth, job creation, and increased profitability of FMCG companies in Indonesia.

Demand forecasting leverages various machine learning approaches, primarily categorized into time series analysis, regression-based techniques, and supervised and unsupervised methods. Time series analysis methods, such as Moving Average (MA) and Auto-Regressive Integrated Moving Average (ARIMA), are commonly employed for forecasting retail Fast-Moving Consumer Goods (FMCG) demand due to their effectiveness in identifying seasonal patterns and behaviors. This study will utilize a range of algorithms, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), ARIMA, Linear Regression (LR), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) models.

2. LITERATURE STUDY

2.1 Demand Forecasting

Demand forecasting is the process of estimating the future demand for a product or service. It is an essential part of supply chain management (SCM), as it is used to make decisions related to procurement, production, and distribution. The accuracy of demand forecasting is crucial in SCM [4] for organizational sustainability, especially in this disruptive era. The key to supply chain efficiency lies in the accuracy of demand forecasting, which plays a vital role in mitigating the bullwhip effect [5].

The bullwhip effect is a phenomenon in supply chains in which the variability of demand increases as it moves up the supply chain from retailers to manufacturers. This is caused by distortions in information flow between different levels of the supply chain. The term "bullwhip" is used to describe the effect because the small fluctuations in demand at the consumer level can cause large swings in production at the supplier level. This effect is also known as "demand amplification," "variance amplification," or the "Forrester effect"[6]. The bullwhip effect becomes significant when the costs of production or order fluctuations are greater than the costs of inventory holding. This phenomenon makes demand forecasting more difficult and inaccurate.

The primary cause of the bullwhip effect is inaccurate demand forecasting. When demand forecasts are inaccurate, businesses at higher levels of the supply chain are more likely to order more products from lower levels. This is because they want to avoid stockouts. However, this action worsens the bullwhip effect.

Traditionally, demand forecasting has been done using either a forward-looking approach (analyzing potential future demand) or using historical data from the past [7]. The limitations of statistical methods and spreadsheets have driven the development of big data-based solutions. In this area, machine learning plays a crucial role. Machine learning algorithms can analyze large amounts of data, identify patterns, and build more accurate forecasting models.

2.2 CRISP-DM

CRISP-DM (Cross-Industry Standard Process for Data Mining) is a structured and comprehensive framework, as shown in Figure 3, designed to effectively guide data mining projects. It comprises six main phases that provide a systematic approach to extracting knowledge from data. Here's a brief overview of each phase:

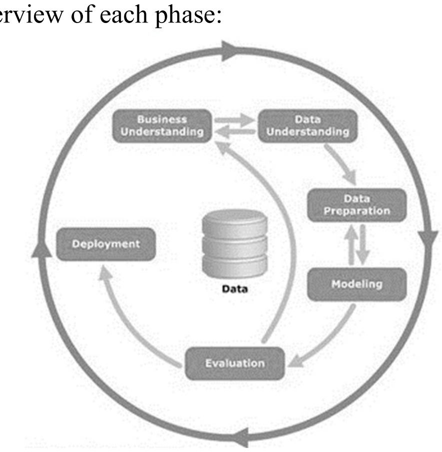

Figure 3: CRISP-DM Framework

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The process begins with Business Understanding, which focuses on clarifying the company's objectives and understanding the available data for the data mining project. This phase identifies what the company aims to achieve through data analysis and determines which datasets will support these goals. Following this, Data Understanding involves thorough exploration of the dataset to uncover its underlying characteristics. Statistical analyses and data visualization techniques are employed to uncover patterns and trends crucial for enhancing forecasting accuracy. Subsequently, Data Preparation ensures the dataset is ready for demand forecasting. This includes cleaning the data to remove inconsistencies, transforming it to a suitable format, and integrating it as needed. The Modelling phase entails constructing machine learning models for demand forecasting.

Various models are tested to identify the most precise one, which is then trained using historical data to learn optimal parameters for generating forecasts. Evaluation assesses the trained model's performance using validation data separate from the training set, employing metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R Square (R2) to gauge accuracy and suitability. Finally, Deployment involves creating reports from the model's outputs and developing strategies for integrating it into the company's operational systems.

2.3 Machine Learning for Demand Forecasting

Machine learning is a promising method that can be used to develop better demand forecasting models than those currently used in supply chain management. Machine learning is a branch of artificial intelligence in which algorithms learn and perform tasks without explicit programming. Machines can automatically learn from raw data to generate predictive models based on pre-designed algorithms.

As discussed in the previous chapter, there are three groups of machine learning approaches that are useful for demand forecasting, which can be classified as: time-series analysis, regression-based techniques, and supervised and unsupervised methods.

- **Time-series analysis** is a method that uses historical data to predict future values of a time series. This method assumes that a time series follows a certain pattern or trend. By understanding this pattern or trend, time series methods can make more accurate predictions. In general, time series methods can be grouped based on the algorithms used, including Moving Average methods and ARIMA methods.

- **Regression-based techniques** are one of the most used time series data forecasting methods. This method uses the relationship between the dependent variable (future time series values) and the independent variables (historical data) to make predictions. There are two common types of regression used for time series forecasting:
  a) **Linear Regression**, this method assumes that the relationship between the dependent variable and the independent variables is linear.
  b) **Non-Linear Regression**, this method does not assume that the relationship between the dependent variable and the independent variables is linear. This method can be used to model non-linear patterns in data.

2.4 Deep Learning for Demand Forecasting

Deep learning is a specialized field within machine learning (ML) and artificial intelligence (AI) that employs artificial neural networks (ANNs) to uncover complex patterns and relationships in data, as illustrated in Figure 4. Inspired by the structure of the human brain, these networks can autonomously extract intricate features and interactions that may be challenging for traditional statistical methods or simpler ML algorithms to detect. This capability makes deep learning particularly effective for analyzing real-world datasets, which often contain hidden insights and exhibit intricate, non-linear relationships. By leveraging hierarchical layers of abstraction, deep learning excels in tasks such as image and speech recognition, natural language processing, and predictive analytics, enabling advancements across diverse domains including healthcare, finance, and beyond.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

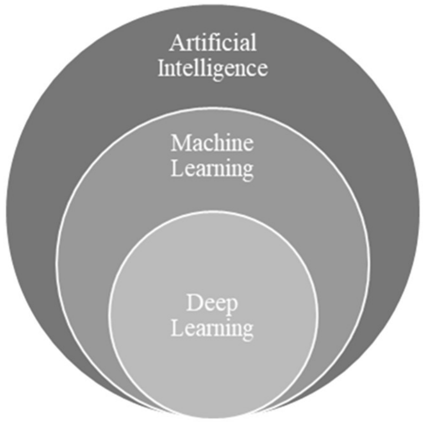

Figure 4: Relationship Between Deep Learning, Machine Learning and AI

Deep learning (DL) is a specialized branch within the field of machine learning (ML). It employs ML techniques to discern intricate patterns within data, utilizing complex artificial neural networks with multiple layers. Machine learning, on the other hand, is a broader subset of artificial intelligence (AI), encompassing various methodologies aimed at imbuing machines with intelligence through learning from data. Both deep learning and machine learning are pivotal in the development of diverse AI applications, leveraging their respective capabilities to tackle complex tasks and improve automated decision-making processes across different domains of artificial intelligence.

2.5 Accuracy Measurement

To measure the accuracy of the demand forecast that has been calculated, this comparison gives us the opportunity to assess the error of the forecast accuracy. And the metrics used to measure accuracy include:

a) RMSE (Root Mean Square Error), Is a metric used to measure model accuracy by comparing predicted values with actual values, expressed as a squared value. The smaller the RMSE value, the more accurate the model. The ideal RMSE value is 0.

b) MAE (Mean Absolute Error), Measuring model accuracy by comparing predicted values with actual values and expressed with absolute values. The smaller the MAE value, the more accurate the model. The ideal MAE value is 0.

c) MAPE (Mean Absolute Percentage Error), Measuring model accuracy by comparing predicted values with actual values. The smaller the MAPE value, the more accurate the model. The ideal MAPE value is 0%.

d) R-Square, Abbreviation for Coefficient of Determination. R-Square measures how much variance in the data is explained by the model. R2 measures how well the independent variable explains variation in the dependent variable. The value ranges between 0 and 1, where the closer to 1, the better the model can explain variations in the data. If the value is 0, it means the model does not make any contribution to explaining the variation in the data.

2.6 Previous Research

In this case, the theory underlying the research is machine learning theory. The research methods used are various machine learning algorithms. And from previous research, in 2016, one of the food retail companies in Germany often experienced food waste and out of stock due to inaccurate demand forecasting [8] resulting in incorrect product orders. Daily demand for fresh food products is influenced by external factors such as seasons, price drops and holidays. To overcome this complexity and inaccuracy, sales forecasting must consider all factors that might influence demand. Research began to develop the SARIMAX model, which attempts to consider all the effects of these factors, to forecast daily sales in retail stores. In 2017 in the same industry, namely retail, research was conducted on the problem of companies losing profitability from losing customers and losing sales potential so that research was carried out to identify early customer churn [9] using deep learning methods, especially CNN (Convolutional Neural Network) & RBM (Restricted Boltzmann Machine).

In the following year, namely 2018, research was conducted on a company in the retail fashion industry where predicting sales of new fashion products was difficult due to short life cycles, external factors, and varying consumer tastes. However, comparing the performance of deep learning with shallow techniques [10] such as Decision Tree, Random Forest, Support Vector Regression, and Linear Regression shows several evaluation metrics that have the potential to be applied to other retail industries with similar characteristics. In 2019, a study of retail banking companies in Poland designed systems to increase the effectiveness of marketing campaigns. The research uses time series data and is classified using random forests and deep neural networks to predict whether customers are interested or not in credit products in a certain time window [11].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

In 2020, a study was conducted to predict retail product purchases by individual customers using machine learning techniques. The goal is to provide personalized discount offers to customers right before they purchase [12], delivered via mobile devices, and reduce paper-based mass marketing. Four main techniques are used, namely RNN (Recurrent Neural Networks), Linear Regression, ANN (Artificial Neural Networks) and Extreme Gradient Boosting. The accuracy of using machine learning promises to make personal marketing more effective and reduce mass advertising waste. In 2021, research was conducted on a packaged food manufacturing company in Latin America. Which discusses solutions to the problem of running out of stock (Out-Of-Stock, OOS) [13] which causes loss of sales and customer satisfaction. This research develops two machine learning-based systems for automatic out-of-stock (OOS) detection. The first system employs a single Random Forest classifier that is trained using balanced data to enhance its predictive performance. The second system utilizes an ensemble classifier that integrates six distinct classification algorithms, aiming to leverage the strengths of multiple models to improve overall detection accuracy.

The next research will be in 2022 regarding the importance of demand forecasting for supply chain management and retail operations. As digital data increases, this research focuses on predictive analysis of retail sales using machine learning techniques [14], Various models were tested in this research, including regression and time series approaches. The regression models explored were Linear Regression, Random Forest Regression, and Gradient Boosting Regression. For time series forecasting, ARIMA and LSTM models were evaluated to assess their effectiveness in predicting demand.

This research succeeded in identifying XgBoost as the best model for retail sales forecasting with a high level of accuracy. The same year, a study investigated the prediction of student enrollments in educational institutions utilizing statistical machine-learning models. The researchers employed two primary models: Auto-Regressive Integrated Moving Average (ARIMA) and Simple Exponential Smoothing (SES). The findings indicated that SES demonstrated superior accuracy compared to ARIMA in forecasting time-series data[15]. Meanwhile, another study presents an architecture to improve predicted resolution times in customer support systems [16]using one-hot encoding and various models. Random Forest outperformed Neural Networks and ADA Boost with enhanced accuracy through extremity features.

In 2023, a study from the United States company Genpact which operates in the field of digital and data services to clients in various industries, conducted research on the importance of accurate food demand forecasting, especially because short product shelf lives and poor inventory management can lead to waste and loss [17]. This research compares various forecasting techniques using machine learning and deep learning for time-based data (time series). The conclusion of this research is that deep learning, especially LSTM, has the potential to be superior in forecasting food demand compared to other regression models.

Similarly, in Indonesia's shrimp industry, accurate sales forecasting for Vannamei shrimp is also critical. Research evaluating machine learning models for shrimp seed sales forecasting identified K-Nearest Neighbors (KNN) as the most accurate model, with an RMSE of 6,326,408.735 and an R^2 of 0.215[18], demonstrating the effectiveness of advanced modeling techniques in improving forecast precision. Meanwhile, another study present assessed six models for predicting closing prices in six Saudi stock market sectors. GRU and Random Forests showed superior performance, while ARIMA consistently underperformed. The research highlights the effectiveness of advanced models[19] like GRU and Random Forests for accurate stock price forecasting and aiding investment decisions. This study explores the use of Gated Recurrent Unit (GRU) neural networks for improving sales forecasting accuracy.

In addition, recent research conducted in 2024 [20] utilized the Long Short-Term Memory (LSTM) method to analyze two years of data on consumer health products. In this study, the products were categorized into four clusters. Out of 59 products, 20 demonstrated high forecasting accuracy (0–25% MAPE) and moderate accuracy (25–50% MAPE), in contrast to only 9 products that exhibited comparable levels of accuracy without clustering.

From a series of research from 2016 – 2024, Table.1 below summarizes previous research regarding demand forecasting in several industrial fields such as retail to provide an overview of the approaches and techniques previously used.

Table.1. Previous Research

Index	***Year***	***Methods***	***Discussion***
[8]	2016	SARIMAX	German Food & Fashion Retail Sales
[9]	2017	CNN, RBM	Retail Industry
[10]	2018	DT, RF, SVR, ANN, LR	Fashion Retail
[11]	2019	RF, NN	Retail Banking
[12]	2020	RNN, LR	Retail Industry
[13]	2021	RF, Logistic Regression, DT, SVR, NN, Ensemble	Food Retail to Latin American Cooking
[14]	2022	LR, RFR, GBR, ARIMA, LSTM	American Retail
[15]	2022	ARIMA, SES	Educational Institution Enrollment Prediction
[16]	2022	Random Forest, Neural Networks, ADA Boost	Customer Support Optimization
[17]	2023	RFR, GBR, LightGBM, XGBoost, CBR, LSTM, BiLSTM	American Service Company (Genpact)
[18]	2023	KNN, SVR, NN	Shrimp Seed Sales Forecasting in Indonesia
[19]	2023	GRU, Random Forests, ARIMA	Stock Price Forecasting in Saudi Stock Market
[20]	2023	LSTM, K-Means	Consumer Health Product Demand Forecasting

3. METHODOLOGY

The conceptual framework of this research presented the logical flow of conducting demand forecasting using machine learning while analyzing the relationships among variables to improve the accuracy of demand forecasting in a case study of an Indonesian FMCG company. This conceptual framework can be illustrated as follows in Figure 5:

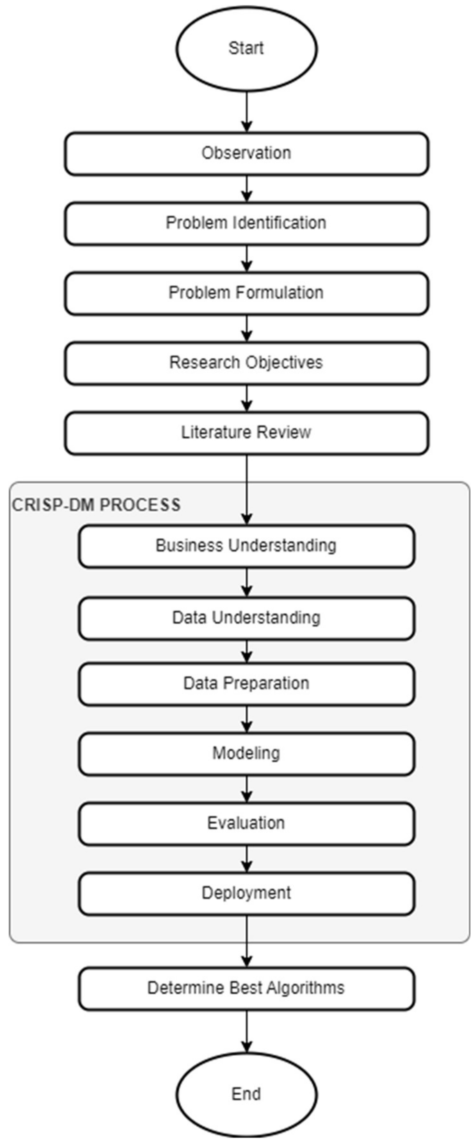

Figure 5: Conceptual Framework of the Research Flow

3.1 Business Understanding

The first stage in the CRISP-DM process involves understanding the goals and requirements from a business perspective, then translating this knowledge into a defined data mining problem. At this stage, it is crucial to develop a clear understanding of how demand forecasting will be utilized according to the users' expectations. This involves identifying the users' needs in forecasting, including the required forecast intervals, the desired forecast horizon or lead time, and the acceptable level of forecast accuracy for decision-making.

In the context of this research, the primary objective is to enhance sales forecasting accuracy using

Journal of Theoretical and Applied Information Technology
31st October 2024. Vol.102. No. 20

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

machine learning models to optimize production and distribution processes, thereby reducing costs and inefficiencies associated with excess or insufficient stock.

3.2 Data Understanding

In the data understanding phase, the data collected uses anonymized historical POS (point of sales) sales data from an FMCG company in the food and beverage sector, starting from January 2015 to October 2023 from several product categories such as biscuits, cereal, beverages, and instant food.

Data collected quantitatively from various categories has several attributes. The number of lines in one category, includes historical sales of +/- 350,000 wholesale, and retail stores spread throughout Indonesia.

Table.2 provides an overview of the product category sales data, including the attribute name, data type, and description.

Table.2. Table Daily Sales

Attribute	Data Type	Description
Year	Integer	Value between 2015 – 2023
Month	Integer	Value between 1 – 12
Week	Integer	Value between 1 – 52
Date	Date/Time	Represents the specific date of the data entry.
Sell Out Qty	Decimal	Value in Carton units
Category	String	Biscuits, Cereal, Beverages, and Instant Food

3.3 Data Preparation

a). Aggregation

To conduct data modeling for predicting monthly sales volumes based on time series analysis, we aggregated sales data across four product categories (Biscuits, Cereal, Beverages, and Instant Food) from 2015 to 2023. Each category encompasses monthly sales represented by the total Sell Out Quantity (Sell Out Qty) for each respective month within the specified timeframe. Data collection yielded an aggregated dataset organized by month and product category. As presented in our analysis, this processed dataset includes 106 data points per category and pertinent additional variables. The metadata for this dataset, including attributes, data types, and descriptions, is summarized in Table 3.

Table.3. Dataset's Metadata After Aggregation

Attribute	Data Type	Description
Year	Integer	Value between 2015 – 2023
Month	Integer	Value between 1 - 12
Sell Out Qty	Decimal	Value in Carton units
Category	String	Biscuits, Cereal, Beverages, and Instant Food

b). Min-Max Scaling

Min-Max Scaling has been meticulously applied based on the dataset provided to standardize the Sell Out (S.O) Qty values across all product categories. This scaling technique normalizes the data by compressing the original values into a range between 0 and 1. By doing so, Min-Max Scaling enhances the comparability of sales figures across different categories, allowing for more effective cross-category analysis within the dataset. Applying this technique ensures that variations in magnitude between categories do not skew the analysis, thus providing a more balanced and fair comparison. The transformed dataset, now equipped with normalized values, is better suited for subsequent analyses, improving processing efficiency and the overall accuracy of predictive modeling efforts. Table 4 presents a sample of the dataset after Min-Max Scaling has been applied, illustrating how the raw sales data has been normalized to facilitate more effective analytical operations.

Table.4. Sample of the Dataset Min-Max Scaled

Year	Month	S.O Qty	Category	S.O Scaled
2015	1	2181588,146	Biscuits	0,17530
2015	2	1582099,203	Biscuits	0,06547
2015	3	2160634,325	Biscuits	0,17146
…	…	…	…	…
…	…	…	…	…
2023	8	4401445,597	Biscuits	0,58198
2023	9	6113432,077	Biscuits	0,89562
2023	10	4969769,597	Biscuits	0,68610

c). Lagging

This research integrates a lag of 3 months into the dataset to enhance its predictive capacity. Table.5 illustrates a sample of the final dataset, highlighting

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the incorporation of lagged variables. In this context, each entry represents the **Sell Out Qty** for a specific month, serving as the target variable for prediction (y). The variables y-1, y-2, and y-3 denote the **Sell Out Qty** from the preceding three months, respectively, utilized as predictors in the analysis. The initial and final three entries of the dataset are excluded due to the lagged period, ensuring the integrity of the time-series modeling approach.

Table.5. Sample of the Dataset Lagging

YEAR	Month	Category	y	y-1	y-2	y-3
2015	1	Biscuits	2181588,146	?	?	?
2015	2	Biscuits	1582099,203	2181588,146	?	?
2015	3	Biscuits	2160634,325	1582099,203	2181588,146	?
2015	4	Biscuits	1848277,157	2160634,325	1582099,203	2181588,146
2015	5	Biscuits	2016143,265	1848277,157	2160634,325	1582099,203
…	…	…	…	…	…	…

d). Time Series Data Splitting for Training and Testing

For this study, the dataset spans from January 2015 to October 2023, encompassing a comprehensive timeframe. Given the nature of time-series data, sequential ordering is crucial for ensuring the accuracy of predictive algorithms. The dataset was partitioned into a training set and a test set, adhering to an 80% to 20% ratio. Specifically, the training set includes data from January 2015 to August 2021, covering most of the dataset. Conversely, the test set comprises data from September 2021 to October 2023, enabling rigorous evaluation of model performance on unseen future data points. This division ensures that the model is trained on historical data and validated on recent observations, maintaining the integrity of time-dependent patterns and trends throughout the analysis.

3.4 Modelling

This research uses several machine learning and deep learning algorithms as a comparison to measure the accuracy of demand forecasting. To train the performance of this algorithm, this research uses Jupyter Notebook tools which are equipped with Anaconda Prompt and installs several libraries such as the open source TensorFlow framework.

For the modeling stages in machine learning starting from dataset initialization to the model evaluation stage where the results matrix uses Root Mean Square Error (RMSE), Mean Absoluter Error (MAE), Mean Absolute Percentage Error (MAPE) and R Square, which can be described as follows:

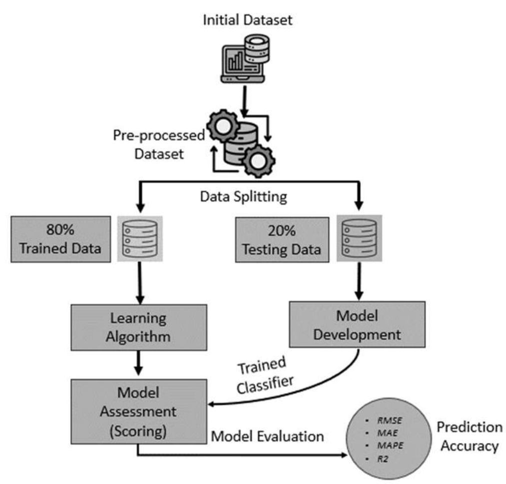

Figure 6. Machine Learning Process Flow

- **Time series method processing flow**. For machine learning algorithms that use several methods such as time series. For this time series method, a collection of data is observed successively over time and is represented as a time series or series of observations taken sequentially within a certain time span. A characteristic feature of time series is the existence of dependencies between adjacent observations. This Dependency is the focus in time series analysis. Understanding these dependency patterns is very important because it makes it possible to:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

a) Predict the future value of a time series based on current and past values.
b) Determine the transfer function of a system that has inertia or inertia, namely a dynamic input-output model that describes the impact of a certain set of inputs on the system output.
c) Using indicator input variables in a transfer function model to analyze and evaluate the influence of unusual intervening events on time series behavior.

To find out the machine learning processing flow, the following is the model processing flow using a machine learning algorithm:

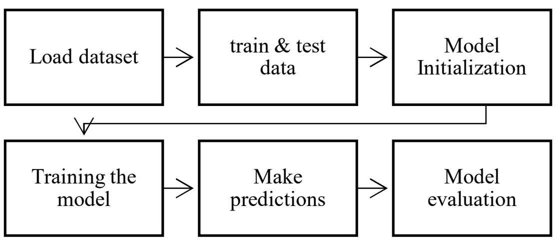

Figure 7. Time-Series Method Processing Flow

- **Regression Method processing flow**, the regression method is basically a statistical technique used to understand the relationship between one or more independent variables (predictor) and the dependent variable (response) with the aim of modelling the pattern of this relationship. It is a statistical model used to predict the dependent variable (y) based on the independent variable (x). The following is the model processing flow using this algorithm:

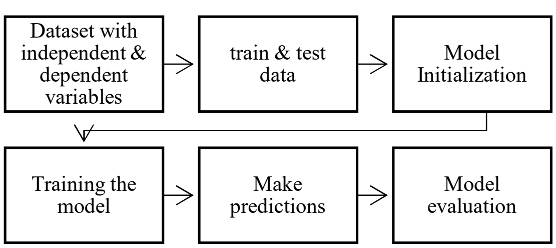

Figure 8. Regression Method Processing Flow

- **Deep Learning Method processing flow**, in general, the machine learning processing flow for deep learning is not much different from the machine learning processing flow for time series and regression. The following is the machine learning processing flow for deep learning:

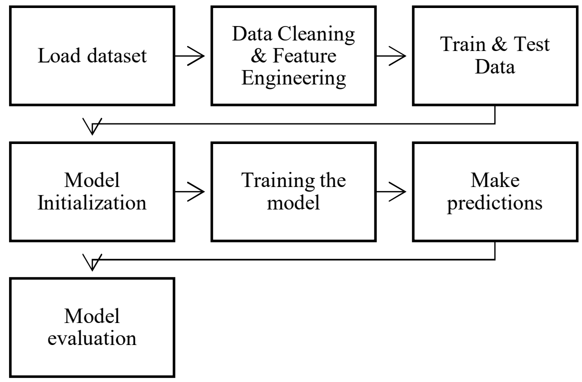

Figure 9. Deep Learning Method Processing Flow

In general, machine learning processing flows for deep learning are more complex than machine learning processing flows for time series and regression. This is because deep learning models have more parameters and require more data to train.

3.5 Evaluation

This section is an important part of the machine learning model development report. This section contains information about the results of model evaluation tests, which are used to assess model accuracy and performance. For table design, the evaluation test report contains the following information:

- **Accuracy measurement method**: Accuracy measurement method per product category used to evaluate the model.
- **Accuracy value**: The accuracy value produced by the accuracy measurement method used.

3.6 Deployment

This stage, which is presented in Figure 10, can be divided into several points, namely:

- **Model review**: this ensures that the model developed meets the criteria for accuracy, precision, and efficiency.
- **Infrastructure development**: this infrastructure consists of hardware, software, and networks.
- **Monitoring and evaluation**: Statistical methods to calculate model accuracy, precision, and efficiency.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

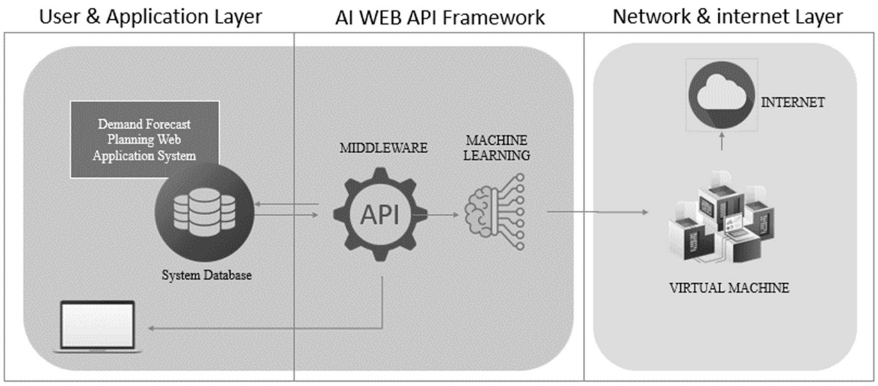

Figure 10. Machine Learning Implementation Design

4. EXPERIMENTAL AND RESULT

4.1 Business Understanding

To efficiently provide consumers throughout Indonesia with a wide variety of FMCG company follows a rigorous planning procedure. For products to be available in retail stores on time, production processes, distribution planning, material requirements planning, and production capacity planning must all be integrated. Inconsistencies during these planning phases may cause delays, which may affect the supply of fresh goods on store shelves.

The forecasting procedure makes use of point-of-sale (POS) data from about 350.000 contemporary wholesale and retail locations in Indonesia that are supported by 8 Distribution Centers (DCs). An FMCG Company ensures effective distribution logistics by satisfying the demand from these DCs.
POS data is saved in Text files in Company Big Data system. It is obtained from several stores and is automatically downloaded every day through a Robotic Process Automation (RPA) system. This system creates baseline forecasts.
To put it simply, an FMCG Company strong distribution and forecasting procedures make sure that the demand for FMCG products from consumers is satisfied effectively. They do this by utilizing sophisticated data analytics and quantitative changes to maintain ideal inventory levels and client satisfaction.

4.2 Data Understanding

This study employs anonymized historical Point of Sales (POS) data from an established Fast-Moving Consumer Goods (FMCG) company within the food and beverage sector. The dataset spans from January 2015 to October 2023, providing a comprehensive view of sales trends over an extended period. The data encompasses a variety of product categories, including but not limited to biscuits, cereal, beverages, and instant food, offering a broad perspective on sales performance across different segments of the FMCG market. Table 6 provides a representative sample of the dataset, showcasing the specific format and content of the collected information to illustrate how the data is structured and what types of details are included.

Table.6. Sample of the Dataset Before Pre-processed

YEAR	Month	Sell Out Qty	Category
2015	1	2,181,588	Biscuits
2015	2	1,582,099	Biscuits
2015	3	2,160,634	Biscuits
…	…	…	…
2023	7	4,540,339	Biscuits
2023	8	4,401,446	Biscuits
2023	9	6,113,432	Biscuits
2023	10	4,969,770	Biscuits

Figure 11 visually explores the trends in sell-out quantity over time for each product category. As the figure shows, the trends exhibit various patterns and fluctuations, reflecting the dynamic nature of consumer demand and seasonal variations.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

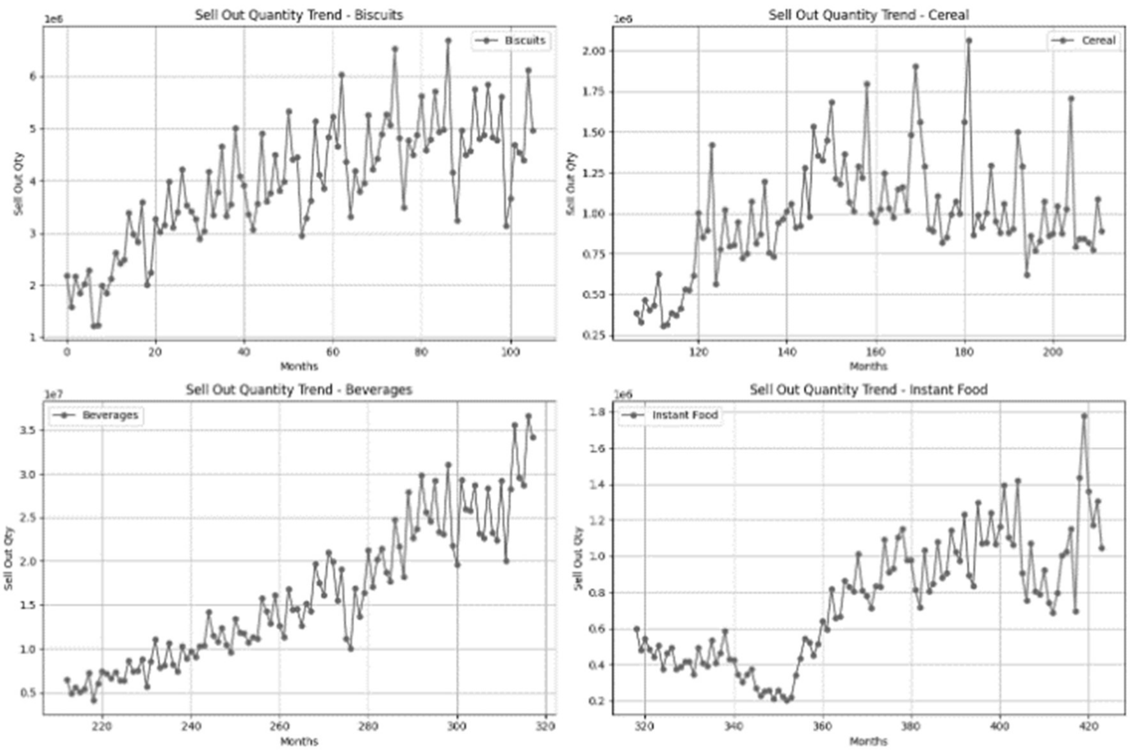

Figure.11. Sales Trend Graph per Product Category

The following table 7 explores the predicted values based for different alpha values ranging from 0 to 1 and involves a trial of alpha values from 0.6 stepping 0.1 to 0.9, evaluating the EMA predictions for each of these alpha values. By systematically testing these alpha values, the table shows how different alpha settings affect the accuracy and reliability of EMA predictions. This provides useful insights into how changing the smoothing factor can impact the results of forecasting.

Table.7. Trial Alpha EMA per Category

YEAR	Month	Sell Out Qty	Category	α=0.6	α =0.7	α =0.8	α =0.9
2015	1	2181588,146	Biscuits	2181588,146	2181588,146	2181588,146	2181588,146
2015	2	1582099,203	Biscuits	1821894,78	1761945,886	1701996,992	1642048,097
2015	3	2160634,325	Biscuits	2025138,507	2041027,794	2068906,859	2108775,703
…	…	…	…	…	…	…	…
2023	7	1361005,781	Instant Food	1144592,088	1118023,037	1093269,046	1069194,734
2023	8	1172427,837	Instant Food	1144592,088	1118023,037	1093269,046	1069194,734
2023	9	1307148,629	Instant Food	1144592,088	1118023,037	1093269,046	1069194,734
2023	10	1044000,799	Instant Food	1144592,088	1118023,037	1093269,046	1069194,734

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4.3 Data Preparation

This study focuses on preparing and analyzing historical point-of-sale (POS) sales data from an FMCG company in Indonesia's food and beverage sector. The dataset spans from January 2015 to October 2023, encompassing four product categories: Biscuits, Cereal, Beverages, and Instant Food. The data preparation steps aim to facilitate accurate time series analysis and forecasting of monthly sales volumes across these categories:

a). Aggregation

Sales data from 2015 to 2023 across four product categories has been aggregated for monthly sales volume prediction using time series analysis. Each category includes monthly Total Sell Out Quantity (Sell Out Qty), meticulously organized by month and category, comprising 106 data points per category. The dataset includes additional variables crucial for comprehensive analysis and forecasting.

b). Min-Max Scaling

Min-Max Scaling has been applied to standardize the "Sell Out Qty" values across all categories in the dataset spanning from 2015 to 2023. This technique compresses the values into a uniform range between 0 and 1, thereby improving comparability among the various product categories.

c). Lagging

We implemented the lagging three-month period into the dataset to significantly enhance the model's predictive capacity. This adjustment integrates historical sales data from the previous three months as additional input features, allowing the model to better account for temporal dependencies and patterns. By incorporating this lagged data, we aim to improve the model's ability to capture trends and fluctuations over time, leading to more accurate and reliable forecasts.

d). Time Series Data Splitting for Training and Testing

The training set spans from January 2015 to August 2021 (80% of the dataset), while the test set covers. September 2021 to October 2023 (20% of the dataset).

4.4 Modelling

The algorithms used in this study are specific to time-series data, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), Autoregressive Integrated Moving Average (ARIMA), Linear Regression (LR), Artificial Neural Networks (ANN), and Long Short-Term Memory (LSTM) networks. These algorithms were compared against the existing forecasting method used.

To achieve high estimation accuracy, the algorithms were fine-tuned by iteratively parameterizing the training process to find the optimal parameters in terms of forecast errors for each combination. The model adjustment (training) process involved dividing the dataset into 4 sub-datasets. Each sub-dataset was further split, with the first 80% of the data used for training to develop the optimal forecasting model.

4.5 Evaluation

To determine the optimal forecasting accuracy testing procedure, each product category is segmented into 4 distinct subsets. Each subset undergoes a validation process where 20% of the data is designated for testing, ensuring robust model evaluation across diverse datasets. This approach is crucial for optimizing forecasting model performance that can be relied upon for each product category, enabling better decision-making in business planning and strategy.

Table.8. Values of the Parameters

Category	Methods						
	SMA	WMA	EMA	ARIMA	LR	ANN	LSTM
Biscuits	n = 3	W_1=0. 2 W_2=0.3 W_3=0.5	α = 0,9	p = 1 d = 1 q = 1	n = 106	Min Scaling = 0 Max Scaling = 1 Lagging = 3	Min Scaling = 0 Max Scaling = 1 Lagging = 3
Cereal	n = 3	W_1=0. 2 W_2=0.3 W_3=0.5	α = 0,9	p = 1 d = 1 q = 1	n = 106	Min Scaling = 0 Max Scaling = 1 Lagging = 3	Min Scaling = 0 Max Scaling = 1 Lagging = 3
Beverages	n = 3	W_1=0. 2 W_2=0.3 W_3=0.5	α = 0,9	p = 1 d = 1 q = 1	n = 106	Min Scaling = 0 Max Scaling = 1 Lagging = 3	Min Scaling = 0 Max Scaling = 1 Lagging = 3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Instant Food	n = 3	W_1=0. 2 W_2=0.3 W_3=0.5	α = 0,9	p = 1 d = 1 q = 1	n = 106	Min Scaling = 0 Max Scaling = 1 Lagging = 3	Min Scaling = 0 Max Scaling = 1 Lagging = 3

Based on the evaluation of machine learning algorithms across various product categories, each method's performance metrics were assessed. The Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R2) were calculated for each method including Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), Autoregressive Integrated Moving Average (ARIMA), Linear Regression (LR), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM).

Table.9. Metric Evaluation Biscuits and Cereal

Methods	Biscuits				Cereal			
	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
SMA	753752.43	626361.51	13.95%	0.25	224.368,84	151.533,71	15,87%	0,23
WMA	562183.28	461029.05	10.20%	0.58	166.569,64	110.033,22	11,53%	0,58
EMA	**112153.80**	**84723.50**	**1.85%**	**0.98**	**32.819,01**	**21.708,39**	**2,28%**	**0,98**
ARIMA	868549.92	674814.75	15.56%	-0.09	264.950,40	222.502,38	24,14%	-0,17
LR	645783.64	505899.45	15.27%	0.67	291.326,89	230.698,46	26,97%	0,35
ANN	0.005	0.003	127.92%	0.99	0,007	0,005	20,92%	0,99
LSTM	0.01	0.005	271.34%	0.99	0,007	0,005	20,40%	0,99

Table.10. Metric Evaluation Beverages and Instant Food

Methods	Beverages				Instant Food			
	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
SMA	3642571.31	3196111.94	11.85%	0.43	201543.21	168885.38	16.18%	0.51
WMA	2723232.21	2370607.95	8.81%	0.68	148600.03	126321.85	12.10%	0.74
EMA	**3383.84**	**2290.67**	**0.24%**	**1.0**	**2920.45**	**2291.91**	**0.22%**	**1.00**
ARIMA	4728796.80	4031369.73	15.44%	0.004	351491.47	306395.4	34.41%	-0.62
LR	4379781.92	3574209.81	12.96%	0.14	317892.41	269327.5	30.18%	-0.33
ANN	0.007	0.003	1.54%	0.99	0.008	0.004	12214652108802%	0.99
LSTM	0.017	0.014	10.04%	0.99	0.021	0.017	24029215550903800%	0.99

Tables 9 and 10 highlight the effectiveness of the Exponential Moving Average (EMA) in enhancing forecasting accuracy in the FMCG sector, consistently outperforming other methods with superior RMSE, MAE, MAPE, and R^2 values in categories such as biscuits, cereals, beverages, and instant foods. In this category, EMA achieved a MAPE of 1.85% for biscuits and 0.22% for instant foods. Meanwhile, Simple Moving Average (SMA) and Weighted Moving Average (WMA) showed decent but less consistent performance, with higher error metrics and lower R^2 values. However, models like ARIMA and Linear Regression (LR) generally performed poorly, exhibiting higher MAPE and lower R^2 values. Additionally, the study found that Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) models showed the worst performance, with extremely high MAPE values and unreliable predictions.

4.6 Deployment

After evaluating the performance of several forecasting models using key metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R2), the optimal deployment

Journal of Theoretical and Applied Information Technology
31st October 2024. Vol.102. No. 20

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

strategy for each product category is determined. The chosen models for deployment are selected based on their superior performance in forecasting accuracy.

The deployment of a machine learning model is a critical phase that follows the model development and evaluation stages. It involves integrating the model into a production environment where it can be used for real-time predictions and decision-making. This process ensures that the model operates efficiently, accurately, and reliably within the system it is designed to enhance. The deployment phase can be broken down into several key steps, each of which is essential for the successful implementation and ongoing performance of the model.

a) **Model Review**: In the evaluation of the models using metrics such as RMSE, MAE, MAPE, and R^2 across various product categories including biscuits, wafers, candies, chocolates, cereals, beverages, instant foods, and coffee, it was observed that models like EMA and ANN performed exceptionally well, demonstrating high R^2 values and low error rates. In contrast, ARIMA and LR showed comparatively lower performance in certain categories.
b) **Infrastructure Development:** Prepare the required hardware, software, and network infrastructure.
c) **Monitoring and Evaluation**: By continuously evaluating these metrics using statistical methods, it becomes possible to gauge the model's performance accurately. Based on these evaluations, retraining the model with new data, and updating it ensures that performance remains optimized or improves over time, aligning with evolving system requirements and user expectations.

4.7 Discussion

Exploring the Advantages of the EMA Model in Capturing Dynamic Demand in the FMCG Sector This aligns with the conclusions drawn by Vanitha and Jayashree (2022), who emphasized the efficacy of statistical models in capturing trends and seasonal patterns in time series data [15]. The consistency of our results with their findings underscores the robustness of the EMA model, particularly in scenarios where demand is subject to rapid fluctuations.

In contrast, the poor performance of the LSTM models, evidenced by their high MAPE values, indicates potential issues such as overfitting and data instability. These challenges are further highlighted by Panda and Mohanty (2023), who observed that complex machine learning models might not always be optimal in time series forecasting within the food demand supply chain context, where regressor analysis proved more effective in certain scenarios[17]. Their findings suggest that while machine learning models like LSTM hold promise, they may require careful tuning and larger datasets to achieve reliable performance, especially in highly variable environments. This comparison highlights the strength of simpler models like EMA over more complex ones like LSTM, especially in highly variable environments.

Furthermore, we have compared our results with other recent studies conducted in various sectors to broaden the scope of the literature survey and add further context for our research contribution. To demonstrate the variety of techniques used for demand forecasting, the updated literature review now includes techniques like SARIMAX (German retail), CNN and RBM (retail industry), and Random Forest, LSTM, and K-Means clustering (consumer health products). This comparison highlights the distinction between our methodology and the importance of EMA's better performance, particularly in the FMCG industry.

Our contribution is to show that whereas increasingly complicated models, such as long short-term memory (LSTM), have been used in many domains, their complexity only sometimes translates into improved demand forecasting ability. This is demonstrated by EMA's higher accuracy in our study, which outperforms standard and complicated models employed in previous research and considerably reduces MAPE in important product categories.

5. CONCLUSION & FUTURE WORK

This study aimed to improve demand forecasting accuracy in the FMCG industry in Indonesia by evaluating the performance of several machine learning models, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), ARIMA, Linear Regression (LR), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) across various product categories. The results provide insights into the performance of these models in demand forecasting for the FMCG industry, with practical and theoretical implications. Understanding these implications can help FMCG companies in Indonesia enhance their demand forecasting accuracy, reduce operational inefficiencies, and optimize costs.

Table.11. MAPE Comparison: Traditional vs. EMA

Category	MAPE	
	Traditional	**EMA**
Biscuits	8.21%	1.85%
Cereal	16.82%	2.28%
Beverages	23.72%	0.24%
Instant Food	30.31%	0.22%

The study's key findings include the superior performance of the EMA method, which significantly improves demand forecasting accuracy compared to traditional methods. For example, adopting EMA can reduce the MAPE in the biscuits category from 8.21% to 1.85%. Table 11 compares traditional forecasting methods with EMA, demonstrating EMA's superior accuracy across various product categories. Furthermore, the study indicates that simpler models like EMA can outperform more complex models such as ANN and LSTM. These findings emphasize the importance of selecting the appropriate forecasting model based on specific product categories to achieve optimal results.

However, the limitations of this study should be acknowledged. Initially, the examination was limited to product categories in Indonesia's FMCG industry, limiting the findings applicability to other sectors. Furthermore, the very short dataset may have restricted the performance of more sophisticated models like Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM). These models often require larger datasets to capture complicated patterns.

Moreover, to improve model performance, future research might broaden the dataset, diversify the product categories, and investigate more extended periods to improve model performance. Investing in enhanced feature engineering methods for intricate models may also increase predicted accuracy. By addressing these issues, demand forecasting models will help produce more accurate and dependable predictions for the FMCG sector.

To support ongoing research, it is recommended that FMCG companies in Indonesia consider implementing advanced machine learning techniques to improve demand forecasting accuracy. Specifically, adopting models like the Exponential Moving Average (EMA), which has shown superior performance in this study, could enhance forecasting precision. Additionally, exploring hybrid models that combine EMA with other machine learning techniques may further optimize forecasting accuracy and operational efficiency.

Future studies should focus on expanding the dataset to include a wider range of historical data and additional product categories. This broader dataset will help models capture more complex trends and seasonal variations, leading to improved predictive accuracy. Furthermore, it is crucial to fine-tune the parameters of complex models such as Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks. Optimizing these models and incorporating new data sources can enhance the accuracy and reliability of demand forecasting models in the FMCG sector, providing more actionable insights for companies.

REFERENCES

[1] P. Tavakkol, B. Nahavandi, and M. Homayounfar, "Analyzing the Drivers of Bullwhip Effect in Pharmaceutical Industry's Supply Chain," *Journal of System Management*, vol. 9, no. 1, pp. 97–117, 2023, doi: 10.30495/jsm.2022.1966147.1691.

[2] M. Abolghasemi, E. Beh, G. Tarr, and R. Gerlach, "Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion," *Comput Ind Eng*, vol. 142, 2020, doi: 10.1016/j.cie.2020.106380.

[3] "Working Capital Report Southeast Asia 2019".

[4] A. M. Aamer, L. P. E. Yani, and I. M. A. Priyatna, "Data analytics in the supply chain management: Review of machine learning applications in demand forecasting," 2021. doi: 10.31387/oscm0440281.

[5] D. Apriyani, R. Nurmalina, and Burhanuddin, "Bullwhip effect study in leaf organic supply chain," *Agraris*, vol. 7, no. 1, 2021, doi: 10.18196/agraris.v7i1.9842.

[6] X. Wang and S. M. Disney, "The bullwhip effect: Progress, trends and directions," 2016. doi: 10.1016/j.ejor.2015.07.022.

[7] M. Seyedan and F. Mafakheri, "Predictive big data analytics for supply chain demand forecasting: methods, applications, and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

research opportunities," *J Big Data*, vol. 7, no. 1, 2020, doi: 10.1186/s40537-020-00329-2.

[8] N. S. Arunraj, D. Ahrens, and M. Fernandes, "Application of SARIMAX Model to Forecast Daily Sales in Food Retail Industry," *International Journal of Operations Research and Information Systems*, vol. 7, no. 2, 2016, doi: 10.4018/ijoris.2016040101.

[9] A. Dingli, V. Marmara, and N. S. Fournier, "Comparison of deep learning algorithms to predict customer churn within a local retail industry," *Int J Mach Learn Comput*, vol. 7, no. 5, 2017, doi: 10.18178/ijmlc.2017.7.5.634.

[10] A. L. D. Loureiro, V. L. Miguéis, and L. F. M. da Silva, "Exploring the use of deep neural networks for sales forecasting in fashion retail," *Decis Support Syst*, vol. 114, 2018, doi: 10.1016/j.dss.2018.08.010.

[11] P. Ładyżyński, K. Żbikowski, and P. Gawrysiak, "Direct marketing campaigns in retail banking with the use of deep learning and random forests," *Expert Syst Appl*, vol. 134, 2019, doi: 10.1016/j.eswa.2019.05.020.

[12] M. Droomer and J. Bekker, "Using machine learning to predict the next purchase date for an individual retail customer," *South African Journal of Industrial Engineering*, vol. 31, no. 3, 2020, doi: 10.7166/31-3-2419.

[13] J. M. R. Andaur, G. A. Ruz, and M. Goycoolea, "Predicting out-of-stock using machine learning: An application in a retail packaged foods manufacturing company," *Electronics (Switzerland)*, vol. 10, no. 22, 2021, doi: 10.3390/electronics10222787.

[14] Dr. M. U. Ashraf, "A Predictive Analysis of Retail Sales Forecasting using Machine Learning Techniques," *Lahore Garrison University Research Journal of Computer Science and Information Technology*, vol. 6, no. 04, 2022, doi: 10.54692/lgurjcsit.2022.0604399.

[15] S. Vanitha and R. Jayashree, "A PREDICTION ON EDUCATIONAL TIME SERIES DATA USING STATISTICAL MACHINE LEARNING MODEL -AN EXPERIMENTAL ANALYSIS," *J Theor Appl Inf Technol*, vol. 100, no. 14, pp. 5189–5200, 2022.

[16] S.-C. Haw, K. Ong, L.-J. Chew, K.-W. Ng, P. Naveen, and E. A. Anaam, "Improving the Prediction Resolution Time for Customer Support Ticket System," *Journal of System and Management Sciences*, vol. 12, no. 6, pp. 1–16, 2022, doi: 10.33168/JSMS.2022.0601.

[17] S. K. Panda and S. N. Mohanty, "Time Series Forecasting and Modeling of Food Demand Supply Chain Based on Regressors Analysis," *IEEE Access*, vol. 11, 2023, doi: 10.1109/ACCESS.2023.3266275.

[18] D. A. Anggraeni and N. Legowo, "APPLICATION OF MACHINE LEARNING ALGORITHMS FOR FORECASTING SALES OF SHRIMP SEEDS," *J Theor Appl Inf Technol*, vol. 101, no. 22, pp. 7061–7070, 2023.

[19] M. G. Alqahtani and H. A. Abdelhafez, "STOCK MARKET PREDICITION USING STATISTICAL & DEEP LEARNING TECHNIQUES," *J Theor Appl Inf Technol*, vol. 101, no. 23, pp. 7808–7825, 2023.

[20] R. F. Busyra and A. S. Girsang, "Applying Long Short-Term Memory Algorithm for Spam Detection on Ministry Websites," *Journal of System and Management Sciences*, vol. 14, no. 2, pp. 1–20, 2024, doi: 10.33168/JSMS.2024.0201.