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Predictive Modeling in Business Analytics: Leveraging AI & Machine Learning

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Abstract: ***Even though business analytics is not a new concept in the corporate world it has been remodeled and updated to keep up with the modern - day competition that exists in present businesses. One such crucial update that business analytics has received is artificial intelligence. Artificial intelligence (AI) is a significant technology with the potential to revolutionize many aspects of our lives. Applications of machine learning (ML) within BA have proliferated in recent years, revolutionizing the process of business decision - making. The traditional business analytics methods focus on statistical approaches towards assessing business performance. However, the predictions made from these methods are highly uncertain. In the present work, we focus on developing a robust prediction model over past sales information using ML techniques. Artificial Neural Networks (BRNN) and Random Forest Models have been chosen in the present study to compare the best ML model for prediction. The accuracy of the model is validated using a 10 - fold Cross Validation (CV) approach. After comparing both the models, BRNN was seen to be more accurate than random forest model by a minute difference. The feature importance from the ML based models is used for suggesting the critical goods for improving the sales in future. Through this study, we would like to signify the role of ML based techniques in BA. The findings will be focused on outlined in terms of the dependability and accuracy of effective prediction and forecasting techniques.***

Keywords: prediction model, sales forecasting, Artificial Intelligence, machine learning, Random Forest, Bayesian regularization neural networks, root mean square error, Tableau sample superstore, RStudio.

1. Introduction

1.1 AI & ML

AI (Artificial Intelligence) is evolving swiftly in the business world and is transforming how businesses operate, make decisions, and interact with customers. In business, AI is evolving in the following ways:

Artificial intelligence is being used to automate repetitive tasks, reducing the time and effort required for manual labor and allowing workers to focus on more strategic and creative work. AI is utilized to predict consumer behavior, preferences, and trends. This allows businesses to make decisions based on data and increase customer satisfaction. AI - powered chatbots are used to manage customer inquiries and provide immediate responses to customers around the clock, seven days a week. AI is used to personalize customer experiences by analyzing data from previous customer interactions, such as preferences and behavior patterns, to provide customized recommendations and offerings. Artificial intelligence is being utilized to detect fraudulent activities, thereby reducing the risk of financial loss for businesses. Artificial intelligence is being utilized to optimize supply chain management, thereby reducing costs, and increasing efficiency. AI is used to facilitate decision making by providing data - driven insights and recommendations.

Machine learning is a subset of AI that allows machines to learn from data without being explicitly programmed. The evolution of machine learning has been driven by advancements in algorithms, computing power, and data availability. In recent years, deep learning, which is a subset of machine learning that uses artificial neural networks to analyze data, has made significant breakthroughs in areas such as image recognition and natural language processing.

1.2 Applications of Machine Learning in Business:

Machine learning can be used to detect fraudulent activities by analyzing patterns in financial transactions. Machine learning has the capability to forecast customer behavior, trends, and preferences, enabling businesses to make data - driven decisions. Machine learning can be used to personalize customer experiences by analyzing data from past customer interactions to provide tailored recommendations and offerings. Machine learning can be used to automate customer service using chatbots and virtual assistants. Machine learning can be used to optimize supply chain management by predicting demand, identifying bottlenecks, and improving efficiency. Machine learning facilitates decision making processes by furnishing insights and recommendations derived from thorough data analysis.

The ability to accurately forecast sales performance is critical for businesses of all sizes and industries. Sales forecasting provides businesses with the insights needed to make informed decisions about resource allocation, production, and marketing strategies. However, conventional approaches frequently depend on manual input and analysis of data, a process that is prone to errors and can consume considerable time. This can lead to inaccurate forecasts and suboptimal business decisions. Traditional methods typically rely on internal sales data and historical trends to make predictions, which may not be sufficient to capture all the factors that impact sales, such as market trends, competitor activity, and customer behavior. Traditional methods are often rigid and inflexible, making it difficult to adapt to changing market conditions and customer behavior. This can lead to missed opportunities and lost sales. Traditional methods often rely on subjective judgments and assumptions, which can introduce bias and lead to inaccurate forecasts. Traditional methods may struggle to handle complex data sets and multiple variables, such as those found in modern sales environments with diverse product offerings, multiple channels, and global markets. Machine learning techniques offer a more advanced approach to sales forecasting by leveraging large amounts of historical data to identify patterns and trends. By developing a robust prediction model over past sales information using machine learning techniques, businesses can improve their sales forecasting accuracy and make informed decisions about future sales performance.

We aim to develop an accurate prediction model using machine learning techniques that can be integrated into existing business analytics tools. We will outline the steps involved in developing the prediction model, including exploratory data analysis, feature selection, data preparation, model selection, training and testing, evaluation, validation, and interpretation. We will also discuss the potential benefits of using a machine learning - based approach to sales forecasting, such as increased accuracy, improved resource allocation, and enhanced decision - making. we will further address the limitations and challenges associated with using machine learning techniques for sales forecasting and suggest possible solutions. Sales forecasting is the process of estimating future sales revenue for a given period of time. It involves analyzing data from past sales trends, market conditions, and other relevant factors to predict future sales. The importance of sales forecasting cannot be overstated as it has a significant impact on a business's success

1.3 Introduction to the prediction models:

In this research paper, we explore the development of a prediction model for sales performance using two machine learning models: Random Forest and Artificial Neural Networks (ANN). Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their outputs to improve the accuracy and robustness of the model. It has been widely used in various applications, such as finance, marketing, and healthcare, due to its ability to handle noisy and complex data. On the other hand, ANN is a deep learning algorithm that consists of multiple layers of artificial neurons, which can capture nonlinear relationships and patterns in data. ANN has been used in many fields, such as computer vision, speech recognition, and natural language processing, because of its capacity to glean insights from vast data and generalize to unseen data.

A Bayesian Regularisation Neural Network (BRNN) is a type of Artificial Neural Network (ANN). BRNNs combine the principles of Bayesian modeling with recurrent neural networks to capture uncertainty in the network's predictions. In a traditional ANN, the weights and biases of the network are fixed parameters, and the network produces deterministic outputs. However, in a BRNN, the weights and biases are treated as random variables and are assigned prior distributions. This incorporation of Bayesian modeling allows the BRNN to provide probabilistic outputs and quantify the uncertainty associated with its predictions. BRNNs are often used in tasks where uncertainty estimation is crucial, such as time series prediction, natural language processing, and reinforcement learning. By considering the uncertainty in the network's predictions, BRNNs can make more reliable and robust decisions, especially when dealing with noisy or incomplete data.

Random Forest is a popular machine learning algorithm for classification and regression tasks, known for its robustness, accuracy, and ease of use. Alternatively, ANN draws inspiration from the intricate structure and functionality of the human brain, known for its ability to capture complex patterns and relationships in data. Using a dataset of past sales information, we compare the performance of the Random Forest and ANN models in predicting future sales trends. We evaluate the accuracy of the models using metrics such as mean absolute error, mean squared error, and R - squared, and identify the strengths and limitations of each model. We also explore the impact of different features on sales performance and examine the importance of feature selection in developing a robust prediction model.

In this research paper, we aim to develop a prediction model for sales performance using Random Forest and ANN and compare their performance on a dataset of past sales information. The findings of this study can provide valuable insights for businesses seeking to optimize their sales performance using machine learning and artificial intelligence.

2. Literature Review

The evolution of AI concepts has been ongoing from the introduction of substantial computatinonal capabilities in 1956. Various proposals of definitions for Artificial intelligence have been put forward by scholars and industry experts, describing it as the empowerment of computers or machines exhibiting cognitive abilities similar to humans to navigate complex situations. AI plays a crucial role in enhancing decision - making processes for businesses, utilizing information, procedures, and computational power to achieve notable advancements in recent times. It includes machine learning, where algorithms process raw data to generate valuable outcomes, assisting in effective decision - making in complex situations.

In the current business environment, the integration of AI is unconventional and non - neutral, presenting challenges across different sectors. It holds particular significance in the context of Industry 4.0, altering operations to impact decision - making and predictions. Additionally, AI has found applications in human resources, especially in recruitment, where it aims to predict job descriptions and identify the most qualified candidates.

The impact of AI on business processes and performance extends to technological advancement, employment prospects, societal embrace and regulatory frameworks. AI, essentially a machine capable of learning from human behavior and simulating intelligent actions, includes machine learning as a subset. Machine learning employs algorithms to discern relationships within data and can be applied to improve marketing functions, predict customer behavior in real - time, and automate processes.

While terms like "AI, " "automation, " and "robotics" are often used interchangeably, they differ in their underlying mechanisms. AI employs algorithms for learning, logical reasoning, and problem - solving, aiming to replicate human cognitive processes. Businesses find AI crucial in marketing strategies and imaging interpretation to minimize human error. AI - integrated Business Analytics utilizes both data and sophisticated analytics methodologies such as machine learning and neural networks to generate diagnostic, descriptive, predictive, and prescriptive insights.

The collaboration between Business Analytics and AI enhances decision - making processes, and governance plays a crucial role in the successful implementation of AI - integrated BA solutions. Quality data is imperative for the development of AI - based business solutions. Machine Learning (ML) identifies areas for improvement to prevent undesired outcomes, with its effectiveness depending on the task, decision - making stage, and technologies used.

Sales forecasting, a critical aspect of business decision - making, involves the application of various data mining techniques. Commonly used for accurate sales projections are the Gradient Boost Algorithm and Artificial Neural Networks (ANN). Predictive analytics, combining data, statistical models, and machine learning, aids in forecasting future events and trends to enhance company performance.

The complexity of the relationship between sales prediction results and influencing factors requires advanced techniques. Bayesian regularization is introduced as a mathematical technique to address overfitting in nonlinear systems, presenting a novel approach for sales prediction research. This proposal suggests that employing multiple methods on the same data can simplify the evaluation of forecast success. Bayesian regularization, with its objective function incorporating residual sum of squares and sum of squared weights, proves effective in minimizing estimation errors and achieving well - generalized models with lower mean squared errors compared to other algorithms for function approximation problems.

S No:	Definition	Author
1.	Artificial intelligence is the aptness to think, overcome difficulties, study, and combine different emotional intelligence like perception, reasoning, remembrance, diction, and organizing.	(Kar, 2022) [1]
2.	AI is a system that affects the way businesses work and how well they do it, mostly in the realm of technical knowledge, approval, social integration, employment oppurtunities, and regulations.	(Cao, 2021; Collins, 2021; Kumar, 2021). [2]
3.	AI helps employees understand and overcome complex problems and makes decision - making easier by providing multiple options.	(Malik, 2021) [3]
4.	AI is also used by companies' human resources departments to review the resumes and select the most suitable candidate.	(Sridevi & Suganthi, 2022; Votto, 2021) [4]
5.	AI, the latest & pertinent concern within Industry 4.0 involves revolutionizing processes through the implementation of AI systems for decision making and forecasting.	(Singh, 2022). [5]
6.	To provide answers to queries such as 'what', 'how', & 'why' in order to yield business advantages, AI systems employ mathematical models to draw conclusions from data, there by enhancing transparency.	(Kar, 2022) [6]
7.	Artificial intelligence (AI) refers to a series of computational technologies that enable us to make rational decisions in difficult circumstances and a variety of settings.	(Tredinnick, 2017) [7]
8.	AI is a device capable of learning from humans and mimic/replicate their intelligent behavior. In contrast, machine learning is a subset of AI that employs algorithms to determine how data and information are related.	(Kotu and Deshpande, 2019) [8]
9.	supervised learning is a technique for developing a learning model capable of making predictions based on unplanned inputs. AI can deliver valuable data by leveraging machine learning and supervised learning techniques for predicting the behavior in real - time process using automation.	(Kotu and Deshpande, 2019)
10.	Despite being used interchangeably, "AI, " "automation, " and "robotics" mean different things. AI employs algorithms to learn a process, while sensors & manual programming are utilized by automation and robots.	(Oswald and Mascarenhas, 2018) [9]

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11.	AI is essential for businesses because it enables them to determine how to market to individuals based on their behavior.	[Zulaikha, S., Mohamed, H., Kurniawati, M., Rusgianto, S., & Rusmita, S. A. (2020). [10]
12.	It is thought that AI can reduce human oversight, thereby increasing the accuracy of imaging interpretation.	(Fazala, 2018). [11]
13.	For firms to achieve success, they must utilize cutting edge technologies like artificial intelligence and big data analytics are utilized to generate and capture value.	(Mikalef & Gupta, 2021; Wamba - Taguimdje, 2020) [12]
14.	AI - incorporated business analytics differs from traditional approaches as it learns from data autonomously, without explicit programming & uses analytics methods like machine learning and deep learning to find rules and patterns.	(Davenport, 2018; Mikalef & Gupta, 2021). [13]
15.	Proper governance is seen as one of the most important parts of a company's implementation of a business analytics system incorporated with AI.	(Krishnamoorthi & Mathew, 2018; Paschen, 2020). [14]
16.	For any AI - based business system to work well, the quality of the data is very important.	(Dubey, 2019). [15]
17.	ML is utilized to identify potential enhancement areas to avoid undesirable or suboptimal outcomes.	Bohanec, M., Borštnar, M. K., & Robnik - Šikonja, M. (2017). [16]
18.	The utility of machine learning relies on the task, the stage of decision - making, and the technology used.	Bohanec, M., Borštnar, M. K., & Robnik - Šikonja, M. (2017).
19.	Even though there have been big improvements in predicting methods and complex statistical methods, forecasting hasn't changed much.	Armstrong (2020) [17]
20.	If small enough, decision trees and decision rules are self - explanatory, but more complicated symbolic prediction models require model - specific or general explanation approaches.	Bohanec, M., Borštnar, M. K., & Robnik - Šikonja, M. (2017).
21.	Neural networks are black - box models. Researchers trying to make these models more transparent focused on their early use and good prediction power.	Bohanec, M., Borštnar, M. K., & Robnik - Šikonja, M. (2017).
22.	Analysis of sales data presents a number of challenges, and the most important aspects of sales functions are identifying product attributes, determining prices, realizing net sales, and launching new products.	Cheriyan, S., Ibrahim, S., Mohanan, S., & Treesa, S. (2018) [18]
23.	The classification of data is crucial for decision - making. Effective business decisions can be made with the aid of an appropriate sales prediction method.	Cheriyan, S., Ibrahim, S., Mohanan, S., & Treesa, S. (2018)
24.	Various data mining techniques can be employed to perform sales forecasting, enabling the prediction of sales at any store on a given day.	Jain, A., Menon, M. N., & Chandra, S. (2015) [19]
25.	The use of sophisticated predictive models is crucial, and the deliverance of valuable insights through analytics is highly dependent on employees with the necessary skill set.	Schmitt, M. (2023). [20]
26.	Artificial Neural network (ANN) models are extensively employed in sales forecasting due to their adaptability in recognizing data patterns.	Tkáč & Verner, (2016) [21]
27.	The random forest algorithm is made by putting together the bagging and random subspace methods. It analyzes and combines the Meta - ensemble machine learning model predictions from multiple decision tree algorithms.	(Breiman (2001)) [22]

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[22] Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.

28.	The subjective forecast method is based on what experts think and how they estimate things. It is very personal and flexible.	Amrutkar, P., & Mahadik, S[23]
29.	The objective forecast method uses raw data to make mathematical and statistical models. It can be used again, but it's not flexible.	Amrutkar, P., & Mahadik, S
30.	The complexity of the relationship between sales prediction outcomes and the factors that influence them, as well as the historical time series data, complex.	Tay and Cao (2001) [24]
31.	Bayesian regularization was developed to diminish the risk of overfitting.	Burden&Winkler,; MacKay (1992) [25]
32.	Bayesian regularized networks penalize excessively intricate models by driving linkage weights to zero.	Ticknor, J. L. (2013) [26]
33.	To optimize the model, BR employs the weights squared and the sum of squared residuals.	Kayri, M. (2016) [27]
34.	Bayesian regularization (BR) exhibits reduced mean squared errors compared to alternative algorithms.	(Demuth, H.; Beale, M.) [28]

3. Objectives of the Research

- To explore various machine learning algorithms and techniques, such as random forest and neural networks (BRNN) predictive modelling techniques, to determine the most effective approach for analyzing large and diverse sales datasets.
- To develop a prediction model using machine learning techniques, specifically Random Forest and Bayesian regularization neural networks, to predict future sales using past sales data.
- To determine the factors that significantly influence sales and assess their contributions to the prediction model's performance.
- To compare the precision and efficiency of the Random Forest and Bayesian regularization neural network models in predicting sales by evaluating the root mean square error (RMSE) of each model.
- To make sure the prediction model works by putting it through its paces with real - world sales data and comparing its results to the real sales data to see how well it helps businesses make decisions.
- To provide insights and recommendations for further improvement and application of prediction models using AI and machine learning for sales forecasting.
- To evaluate the generalizability of the prediction models using cross - validation techniques and assess their ability to make accurate predictions on unseen data.

3.1 Statement of the Problem:

Using machine learning for business analytics to build a prediction model, the problem statement is to effectively forecast future sales using historical data. Businesses in many diverse fields rely on sales forecasts a lot to plan inventory, distribute resources, and make strategic decisions. Traditional statistical methods for making predictions, on the other hand, don't always take into account the complicated relationships between variables in large and varied datasets. This means that we need an approach based on machine learning that can effectively learn patterns from sales data from the past and make accurate predictions about sales in the future. The challenge is to make a strong prediction model that can deal with different datasets with many variables, such as sales data and other things that may affect sales.

To solve this problem, more research needs to be done on advanced machine learning algorithms and techniques for analysing large datasets, such as random forest, neutral networks, and other predictive modelling techniques. To make sure that the predictions are accurate and can be relied on, the research must also look into data quality, feature selection, and model validation. The ultimate goal is to create a strong and scalable machine learning - based prediction model that can give businesses useful information and help them make smart decisions about their future sales.

3.2. Scope of the Study

The goal of the study is to create a prediction model utilizing past sales data from a given time frame (for four years). Only historical sales data from this time period will be used for the analysis. The study will make use of sales information gathered from a specified source (such as corporate records or web databases). It won't need conducting surveys or conducting interviews to gather fresh primary data. The study will pay particular attention to creating prediction models with the help of the ML algorithms Random Forest and BRNN (ANN). The scope of this study may not cover other ML or AI methods. Data on previous sales will be the primary factor in the analysis used to forecast future sales. If judged pertinent and present in the dataset, other variables may be used, such as product features, pricing information, or customer demographics. Based on accepted evaluation measures like Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), or Root Mean Squared Error (RMSE), the study will assess the effectiveness of the prediction models. Based on the available interpretability approaches for each model, the study will evaluate and assess the clarity of interpretation between the Random Forest and

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BRNN (ANN) models. The discussion will concentrate on the interpretability advantages and disadvantages of each model. The study will concentrate on the use of the prediction models in a particular sector or area of business (such as retail or e - commerce). The conclusions and suggestions might only apply to this particular industry's setting.

3.3. Hypothesis

In the present study, two prediction models that are, random forest and BRNN have been developed using previous sales data and compared in terms of accuracy and precision. When compared, BRNN was seen to be more accurate than random forest by a minute difference.

3.4. Questionnaire Design:

The questionnaire included demographic information of the participants. The circulation of the survey was made within BBA/MBA students to get accurate survey responses. The survey included questions of different nature such as, to analyze the basic understanding of the participants about artificial intelligence and machine learning, how familiar the participants were with random forest and ANN, to know the participants perspective about the application and consequences of AI and ML, to understand their real - life experience in using prediction models. The participants were also asked to give their point of view on what is the most essential feature in a prediction model that will make it more helpful and user - friendly.

3.5. Research Methodology

Data gathering: The first step comprises acquiring sales data from various sources, including prior sales data, market patterns, and customer behavior. It is necessary to organize the data so that machine learning algorithms can use it. The past sales data is obtained which is Secondary data from Tableau sample superstore, which includes monthly sales data from January to December for four years (2019 - 2022).

Data preparation: Data cleaning and pre - processing are required to remove any errors, outliers, or missing data from the collected data. The data should also be normalized or scaled to guarantee that all variables are on the same scale. Data preprocessing steps are conducted, including handling missing values and encoding categorical variables.

Purposive Sampling: Purposive sampling involves selecting units for a sample based on specific characteristics needed, with units deliberately chosen to fulfill a particular objective.

Sample Size: The sample size in this case would depend on the number of monthly sales data points available for the four - year period (2019 to 2022). There is a monthly sales record for each of the 48 months (12 months * 4 years), the sample size would be 48. Each month's sales data would represent one observation in the dataset.

Model selection: Several machine learning algorithms and techniques, including Random Forest and neural networks (BRNN), will be studied in order to determine the most effective strategy for analyzing the sales data and delivering accurate forecasts. Random Forest and Bayesian Regularization Neural Network (ANN) have been selected to develop prediction model.

Model Development: The dataset is divided into training and testing sets. Feature selection techniques are applied to identify relevant predictors. The Random Forest and Bayesian Regularization Neural Network models are implemented using RStudio, with appropriate tuning of model parameters.

Model training and testing: A subset of the sales data will be utilized for training (70%) and testing (30%) in order to evaluate the precision and dependability of the selected machine learning method.

Model evaluation: The performance of the models is evaluated using the RMSE (root mean squared error), correlation coefficient, correlation, MAPE (mean absolute percentage error), and MAE (mean absolute error) metrics. A comparison is made between the RMSE, R^2, MAPE, MAE values of the Random Forest and Bayesian Regularization Neural Network models. Statistical analysis is conducted, to determine the significance of the difference in performance.

Validation: Cross - validation techniques, like 10 - fold cross - validation, are employed to assess the robustness of the models and their ability to generalize to unseen data. Using actual sales data, the prediction model will be put to the test to see if it can provide meaningful insights for corporate decision - making.

Survey: A quantitative method that is a survey was circulated as google forms among BBA/MBA students to understand the extent of knowledge or awareness they have on AI and ML and to understand their experience using these prediction models.

3.6. Limitations of the Study

Poor data quality, such as missing values, outliers, or inconsistencies, can introduce biases and affect the performance of the prediction models. Lack of contextual information: The absence of additional contextual information (e. g., economic factors, market trends) that could influence sales may limit the models' predictive capabilities.

How well the prediction model works may depend on how well the algorithm is made.

Sales patterns can be influenced by various external factors, such as seasonality, market trends, or sudden events (e. g., pandemic). Failure to account for these external factors in the prediction models may limit their accuracy and applicability. Unpredictable events or changes in the business environment during the study period may invalidate the assumptions made by the models or render the training data less representative of future sales.

The findings and conclusions of the study may be limited to a specific industry or product category, as different industries may exhibit unique sales patterns and characteristics.

The prediction models developed using specific sales data may not generalize well to different markets, geographical regions, or time periods, as the underlying dynamics may vary.

The participants of the survey only included those with BBA and MBA as their educational background, so that the outcomes of the survey would be more accurate. Due to this reason there were limited responses.

4. Analysis and Interpretation

4.1. Bayesian regularization of neural networks:

Artificial neural networks function as universal approximators for difficult functions, obtaining non - linear relationships responsively through activation functions. ANNs comprise processing of elements (neurons) operating in parallel and organized by layers, neurons, connection strengths, and activation functions. Back Propagation Neural Networks, a well - known ANN technique, utilizes supervised learning using gradient descent to enhance the network for unfamiliar samples. However, challenges arise with overfitting and overtraining, resulting in noise tuning and a loss of generality.

In order to tackle overfitting, Bayesian regularization is implemented, considering weights as random variables characterized by a probabilistic nature. In normalized Bayesian networks, models with excessive complexity are penalized, reducing unnecessary association weights. The study presents the development of a Bayesian Regularized Neural Network (BRNN) prediction model using R studio. The model utilizes monthly sales data from a sample superstore spanning 4 years, obtained through Tableau, a data visualization and business intelligence tool. The dataset is divided into 70% for training and 30% for testing, aiming to enhance prediction accuracy while addressing overfitting concerns within the dynamic stock market environment.

Code Description:

1) ***Library Imports:***
- The code begins by importing several R packages using the `library () ` function. These packages provide various functions and capabilities used throughout the code.

2) ***Loading Data:***
- The `read_excel () ` function from the `readxl` package is used to read an Excel file named "sales_data. xlsx" from the specified path.
- The data from "Sheet3" of the Excel file is loaded into the `sales_data` data frame.

3) ***Data Preparation:***
- The code selects specific columns (3 and 4 to 20) from the `sales_data` data frame using indexing and assigns the resulting subset to a new data frame called `sample2`.
- The matrix `x` is created by excluding the first column (column 2) from `sample2`.
- The response variable `y` is extracted from `sample2` and stored in a separate vector.
- The predictor variables (`x`) and the response variable (`y`) are combined into a new data frame called `dataset` using the `cbind () ` and `data. frame () ` functions.

4) ***Train - Test Split:***
- The `sample () ` function is used to generate a random vector `ind` of length equal to the number of rows in `dataset`
- Each element in `ind` is assigned a value of 1 or 2 with probabilities specified as `prob = c (0.7, 0.3) `, resulting in a 70: 30 split for train and test data, respectively.
- The train data set is created by subsetting `dataset` where `ind` is 1, and the test data set is created by subsetting `dataset` where `ind` is 2.

5) ***Neural Network Training:***
- The `trainControl () ` function is used to define the control parameters for model training using cross - validation.
- The `train () ` function is called with the training data (`train`), response variable (`y`), method set to "brnn" (Bayesian Regularized Neural Network), and the previously defined control parameters (`trControl`).

6) ***Model Evaluation:***
- The `predict () ` function is used to obtain predictions from the trained model (`fit. brnn`) for the test data set (`test`).
- Various evaluation metrics are calculated using functions from different packages, such as RMSE (root mean squared error), correlation coefficient, correlation, MAPE (mean absolute percentage error), and MAE (mean absolute error).
- The minimum and maximum predicted and observed values are also computed.

7) ***Variable Importance Plot:***
- The `varImp () ` function is used to calculate the variable importance of the trained model (`fit. brnn`).
- The `plot () ` function is called to generate a plot based on the variable importance results. The resulting plot is displayed and saved as a TIFF file.

8) ***Predicted vs. Observed Plot:***
- The `ggplot () ` function from the `ggplot2` package is used to create a scatter plot.
- The observed values are plotted on the x - axis, and the predicted values are plotted on the y - axis.
- The `geom_point () ` function adds points to the plot, while `geom_smooth () ` adds a linear regression
- line.
- Various formatting options, such as titles, limits, labels, and themes, are set using the `ggtitle () `,
- `xlim () `, `ylim () `, `xlab () `, `ylab () `, and `theme () ` functions.
- The resulting plot is displayed and saved as a TIFF file.

The following is the obtained output:

Table 4.1.1: BRNN Evaluation Metrics

Evaluation Metric	Value
R2	0.994
RMSE	2976.37
MAPE	0.13
MAE	2021.52

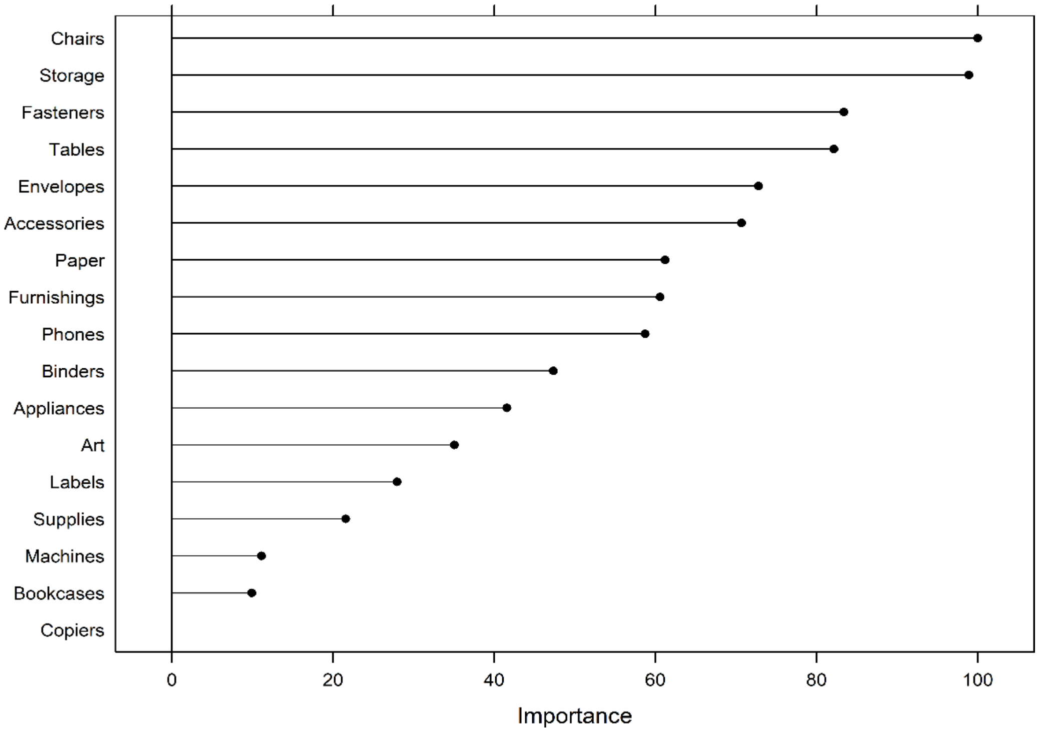

Figure 4.1.1: Variable Importance

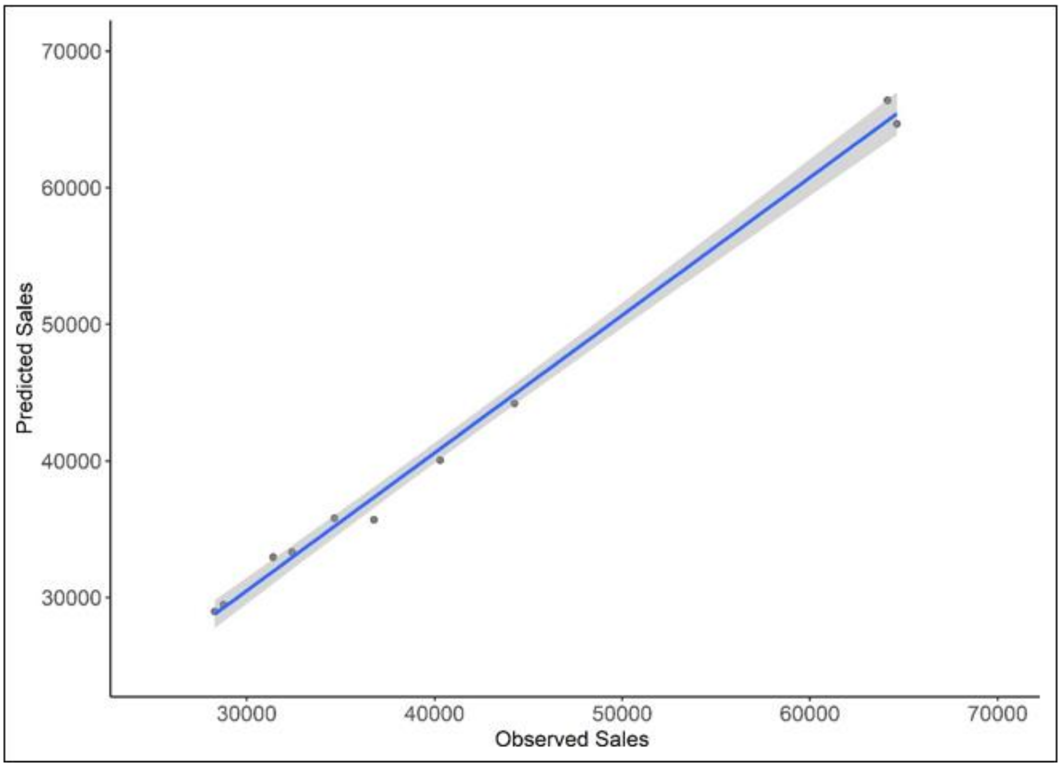

Figure 4.1.2: Observed vs Predicted Sales

4.2 Random forest

This method, which was created to increase the accuracy of decision trees (DT) and get around issues such excessive sensitivity to minute alterations in data, stems from decision trees (DT). It is based on the calculation of an ensemble of trees, then the average prediction value made at each tree's final node and eliminates the lack of robustness shown by a single decision tree. Each tree is generated using a subset of independent variables that are chosen at random in this method. In terms of parameter tuning, values ranging from 1 to the total number of predictors considered in the variable combination under study were evaluated for the number of variables randomly sampled at each split, while the number of trees to grow was tested from 500 to 3000.

Code Description:

1) Library Imports:

- Several libraries are imported using the `library () `

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function, including `dplyr`, `caret`, `mgcv`, `randomForest`, `xgboost`, `readxl`, `MLmetrics`, and `Metrics`.

2) ***Data Import and Preparation:***
- the code uses the `read_excel () ` function from the `readxl` library to read an Excel file named "sales_data. xlsx" located in the "mani" directory. The data from the third sheet ("Sheet3") is read into the `sales_data` variable.
- The `sample2` variable is created by selecting specific columns from the `sales_data` dataset, including column 3 and columns 4 to 20.
- Predictor variables (`x`) are extracted from `sample2` by selecting columns 2 to 18.
- The response variable (`y`) is extracted from `sample2` and corresponds to the "Grand_Total" column.
- The predictor variables (`x`) and the response variable (`y`) are combined into a new dataset called
- `dataset` using the `cbind () ` and `data. frame () ` functions.
- A summary of the `dataset` is displayed.

3) ***Train - Test Split:***
- The dataset is split into a training set (`train`) and a testing set (`test`) using the `sample () ` function. The split is performed with a 70% training and 30% testing ratio.
- The random seed is set to 10000 to ensure reproducibility.
- A `trainControl` object named `control` is created for cross - validation. It uses 10 - fold cross - validation.

4) ***Random Forest Parameter Tuning:***
- The `tuneRF () ` function from the `randomForest` library is used to tune the random forest model's parameters. It searches for the optimal value of `mtry` (the number of variables randomly sampled at each split) by evaluating the out - of - bag (OOB) error estimate.
- The `tuneRF () ` function is called with the training predictors (`train [, 2: 18]`) and the training response (`train$y`).
- The tuning parameters include `mtryStart` (the range of `mtry` values to consider), `ntreeTry` (the number of trees to grow), `stepFactor` (the factor by which the `mtry` range is expanded), and `improve` (the minimum improvement in the OOB error to continue growing the forest).
- The resulting tuning information is stored in the `mtry` variable, which contains the values of
- `mtry` and their corresponding OOB error rates.
- The best `mtry` value is extracted from the `mtry` variable based on the minimum OOB error rate and stored in the `best. m` variable.

5) ***Random Forest Model Training and Evaluation:***
- Another `trainControl` object named `control` is created for model training using repeated cross - validation.
- A `tunegrid` is created with a single value for `mtry`, which is set to 7.
- An empty list called `modellist` is created to store the trained random forest models.
- A loop is performed to train multiple random forest models with different values of `ntree` (the number of trees). The loop iterates over values of 1000, 1500, 2000, 2500, and 3000.
- Inside the loop, the `train () ` function from the `caret` library is employed to train a random forest model (`method = 'rf'`). The response variable is specified as `y` (Grand_Total), and all other variables are used as predictors (`. ` notation).
- The model is trained using the training dataset (`train`), the performance metric is set to RMSE, the tuning grid is set to `tunegrid`, and the `control` object is passed for cross - validation.
- The trained model is stored in the `modellist` list using the `ntree` value as the key.
- After the loop, the performance of the trained models is evaluated using the `resamples () ` function, which calculates various performance metrics using cross - validation.

6) ***Predictions and Evaluation:***
- The `predict () ` function is used to generate predictions (`predicted`) for the testing dataset (`test`) using the best model (`fit`) obtained from the previous step.
- The observed values from the testing dataset are extracted into the `observed` variable.
- Various performance metrics such as RMSE, correlation coefficient, correlation, MAPE, and MAE are calculated using the predicted and observed values.
- The minimum and maximum values of the predicted and observed values are also calculated.

7) ***Plotting:***
- The `rf_data` dataframe is created by combining the predicted and observed values.
- A scatter plot (`rf_plot`) is created using the `ggplot2` library to visualize the relationship between observed and predicted sales values. The plot includes a smooth line fit.
- The plot is customized with titles, axis labels, and annotation.
- The plot is saved as a TIFF image file named "obs_pred_rf_fit. tiff".

8) ***Variable Importance:***

- The variable importance of the random forest model (`fit`) is calculated using the `varImp () ` function from the `caret` library.
- A bar plot showing the variable importance is created using the `plot () ` function.

The following is the obtained output:

Table 4.2.1: Random Forest Evaluation metrics

Evaluation metric	value
R2	0.92
RMSE	14460.41
MAPE	0.32
MAE	10703.59

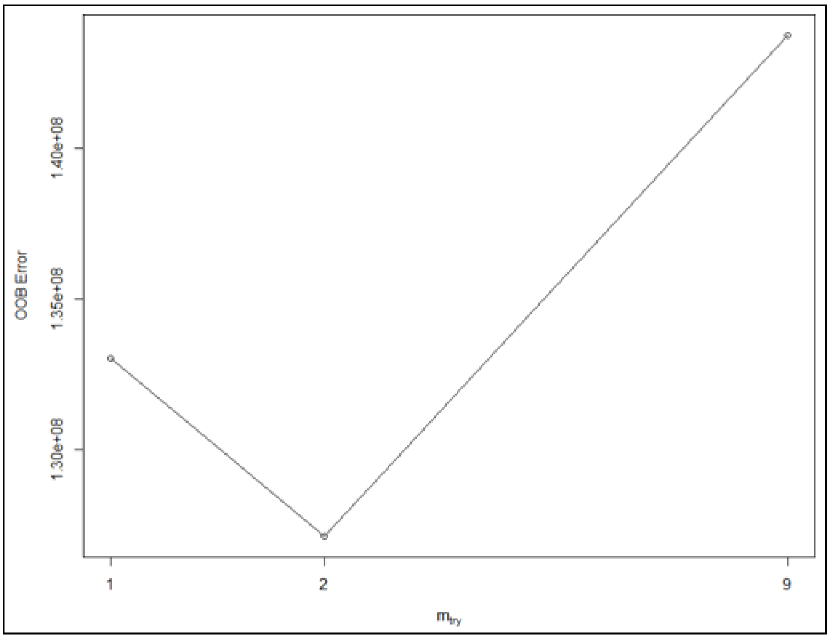

Figure 4.2.1: OOB Error

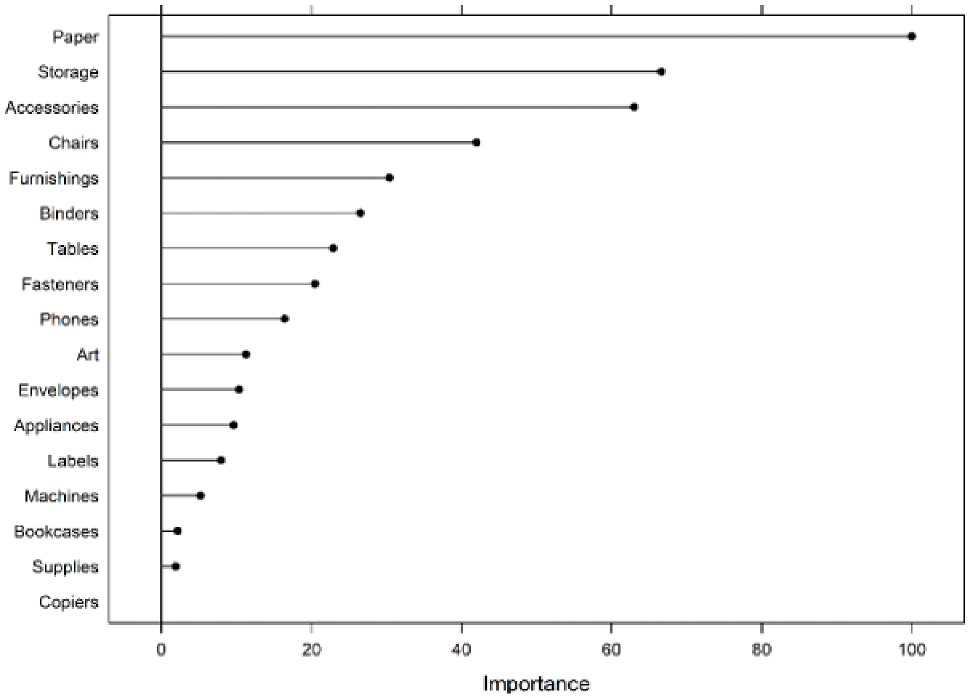

Figure 4.2.2: Variable Importance

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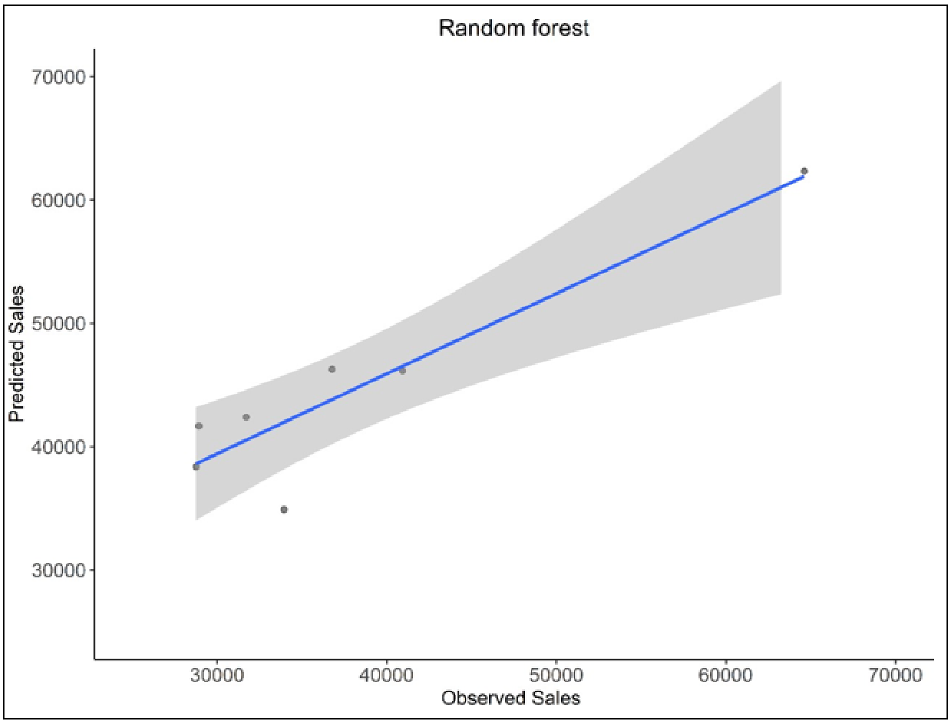

Figure 4.2.3: Observed vs Predicted Sales

4.3 Comparison of both the prediction models:

The final and crucial step is evaluating the model's performance through prediction to gauge the accuracy of future sales forecasts. The R, R^2, MAE, MAPE and RMSE of the predicted sales compared against observed sales for BRNN are 0.997, 0.994, 2021.52, 0.13, 2976.37 respectively. The R, R^2, MAE, MAPE and RMSE of the predicted sales compared against observed sales for RF are 0.96, 0.92, 10703.59, 0.32, 14460.41, respectively. The results show that, the BRNN have a high capability to predict the sales of a product (R^2= 0.99). From the line graph analysis, it becomes evident that BRNN stands out as the most effective machine learning algorithm for sales prediction, as it exhibits the lowest root mean square error in comparison to other algorithms. For that reason, the proposed models can be considered as powerful tools for supporting the decision - making process of the company. These findings show that BRNN can beat most shallow strategies when used to analyze smaller datasets, despite being advised for doing so when analyzing databases with lots of data. From a managerial perspective, the ideal technique should strike a balance between the models' performance, interpretability, and understandability. In this specific instance, the organization may have to put out a lot of work to comprehend the technique and the parameter tweaking needed before adopting a decision support tool based on BRNN. Contrarily, methods like RF are extremely understandable, offer findings that are generally satisfying, and shed light on how the predictive variables affect the effectiveness of the models.

Table 4.3.1: Comparison Table

Evaluation Metric	Regression Technique	
	BRNN	RF
R2	0.99	0.92
RMSE	2976.37	14460.41
MAPE	0.13	0.32
MAE	2021.52	10703.59

4.4 Survey Analysis

The survey was created using google forms, which is a useful platform for researchers using quantitative methods such as surveys. There was a total of 25 responses who varied in age groups. The majority of the participants belonged to the 18 – 25 age group. All the participants belonged to the educational streams of BBA/MBA; this was done due to the fact that people outside these educational streams would not have the knowledge to answer the technical questions which required the participant's opinion as well as their experience working with these prediction models.

It was observed that although most of the participants were aware of the concepts of artificial intelligence and machine learning, not as many were familiar with the techniques random forest and ANN. The participants were asked about their opinion on what the potential benefits of AI and ML in business operations. To which, the majority responses reflected that there would be improved accuracy in decision making. The other options that were included in the question were, improved efficiency and productivity and improved customer satisfaction. There were few responses supporting the option of improved efficiency and productivity as well but very few had the opinion that AI would improve customer satisfaction.

The survey also had a question where it asked the participants if AI and machine learning are a potential threat to cause job loss to human workers in some industries. This has been a hot topic of debate in recent times. The majority of the responses agreed that it would eventually replace human workers in some industries. there were contradictory responses where the participants thought that AI and Machine learning would ease the work of human workers and not totally replace them. It can be analyzed that AI and machine learning will not totally replace human workers but might reduce the number of human workers required to get a task done. When asked about the potential drawbacks of AI and machine learning the majority of the participants responded saying that there would be bias and discrimination. Analyzing the reflected the responses it can be said that, AI and ML algorithms are developed using training data, which is often sourced from real world data that reflects human biases and social prejudices. If the training data is biased, the AI system can inadvertently learn and perpetuate those biases in its prediction or decision making. Addressing bias in AI and ML systems is crucial to ensure fairness and prevent discrimination. it is important to recognize that addressing bias in AI is a continuous and complex challenge. It neccesitates a blend of technical solutions, diverse perspectives, and ethical considerations to ensure that AI system are developed and deployed in a responsible and unbiased manner.

It was also observed that many participants have not used past sales for their business predictions and neither explored AI or machine learning technique. Even though there were only few that have previously used AI and ML for business predictions, they too did not have a very good experience with AI and ML's accuracy in predicting sales as majority of them said there was only some accuracy to the prediction. Despite of the less accuracy, most of the participants still wanted to use AI and ML in their future for sales prediction as it is an effective tool which will help make better decisions. When asked what the most important traits within a predictive model, majority of the participants chose accuracy and some also chose ease of use and customizability.

It was analyzed from the survey that majority of the participants did not face any challenges or obstacles when working with AI and ML such as data security and privacy. There were few responses that stated that they faced a challenge of missing data or inconsistent data. To address these challenges, it is essential to employ appropriate data processing techniques. Additionally, regular monitoring and validation of the predictive models using real - time data can help identify and address any shortcomings or changes in the underlying patterns.

5. Summary of Findings

The objective of this research was to develop a prediction model for sales using past sales data, employing Artificial Intelligence (AI) and Machine Learning techniques. Specifically, the study compared the performance of two models: Random Forest and Bayesian Regularization Neural Networks (ANN).

The dataset used for the research consisted of historical sales records and relevant features. The models were trained and evaluated using this dataset to assess their predictive accuracy.

Upon analyzing the results, it was observed that the Bayesian Regularization Neural Network model outperformed the Random Forest model in terms of accuracy. This conclusion was drawn based on the evaluation metric of root mean square error (RMSE). The Bayesian Regularization Neural Network achieved the lowest RMSE, indicating that it provided more accurate predictions of sales compared to the Random Forest model.

This finding suggests that the Bayesian Regularization Neural Network approach, with its ability to grasp intricate patterns and connections within the data, is better suitable for developing a robust sales prediction model. The model's capability to effectively handle non - linear relationships and its flexibility in adapting to diverse data patterns contribute to its superior performance.

The results of this research have significant implications for businesses and organizations involved in sales forecasting. The adoption of the Bayesian Regularization Neural Network model can result in further precise predictions, enabling decision - making based on thorough information, optimized inventory management, and improved resource allocation. The higher accuracy of sales predictions can assist businesses in optimizing their production levels, supply chain operations, and marketing strategies, ultimately leading to increased profitability.

While the research establishes the superiority of Bayesian Regularization Neural Networks over Random Forest for sales prediction, it also identifies opportunities for future exploration. Further studies can investigate the performance of alternative AI techniques, such as deep learning algorithms or ensemble methods, to evaluate their suitability for sales prediction tasks.

Additionally, future research can focus on exploring additional features or variables that could enhance the precision of sales forecasting models. By including more relevant information, such as economic indicators, seasonality, or customer demographics, the predictive capability of the models may be further improved.

Moreover, the developed prediction model could be evaluated in practical circumstances to evaluate its applicability and effectiveness. By testing the model with real - time sales data and comparing its predictions against actual sales outcomes, the practical viability and robustness of the model can be verified.

6. Recommendations and Conclusions

6.1. Recommendations

- Use the developed prediction model as part of your business's decision - making process to improve the accuracy of sales forecasts.
- Give the staff regular training to keep them up to date on the latest techniques and methods for machine learning.
- Create an automated sales forecasting system that can work with the business analytics tools you already have. This will make forecasting more accurate.
- Investigate different hyperparameter configurations and regularization techniques within the Bayesian Regularization Neural Network to optimize its performance even further.
- Explore variations of Bayesian Neural Networks, such as Variational Inference or Monte Carlo Dropout, to assess their performance in comparison to the Bayesian Regularization Neural Network.

- Assess whether an ensemble of the two models can further improve prediction accuracy and provide more robust results.
- Assess the performance of the Bayesian Regularization Neural Network and Random Forest models on different segments or subsets of the sales data, such as specific product categories or geographical regions.
- Validate the accuracy and effectiveness of the models in a practical business setting by comparing the predicted sales with the actual sales data.
- Evaluate the models' performance over an extended period to assess their stability and adaptability to changing market conditions.
- Compare the Bayesian Regularization Neural Network and Random Forest models with other popular ML models, such as Support Vector Machines, Gradient Boosting, or Long Short - Term Memory (LSTM) networks, to evaluate their relative performance in sales prediction.

6.2. Conclusion

Based on the research conducted on developing a prediction model using past sales data with the help of Artificial Intelligence (AI) using Machine Learning (ML) models of Random Forest and (ANN) Bayesian Regularization Neural Networks, the findings indicate that the Bayesian Regularization Neural Network outperformed the Random Forest model regarding predictive precision. The evidence supporting this conclusion is based on the lowest Root Mean Square Error (RMSE), MAPE, MAE and higher correlation, R^2 values achieved by the Bayesian Regularization Neural Network.

The study utilized historical sales data and implemented both the Random Forest and Bayesian Regularization Neural Network models to predict future sales. The evaluation metrics, including RMSE, R^2, MAPE, MAE were used to assess the performance of the models. The Bayesian Regularization Neural Network consistently exhibited lower RMSE, MAPE, MAE and higher correlation, R^2 values compared to the Random Forest model.

These findings highlight the superior predictive capabilities of the Bayesian Regularization Neural Network in apprehending intricate patterns and relationships within the sales data. The model's capacity to incorporate regularization techniques and handle uncertainties effectively might contribute to its enhanced accuracy.

The implications of these results are significant for businesses relying on sales forecasting for decision - making. The Bayesian Regularization Neural Network can provide more reliable and precise predictions, allowing companies to make informed decisions regarding inventory management, resource allocation, and strategic planning. By leveraging the power of AI and ML, businesses can potentially optimize their operations and improve overall performance. However, it is important to acknowledge the limitations of the study. These may include data constraints, assumptions made during model development, and potential biases. Furthermore, the comparison focused on Random Forest and Bayesian Regularization Neural Networks, neglecting other ML models that could also demonstrate competitive performance.

Future research should explore additional ML models, expand the scope of data sources, and consider incorporating external factors such as economic indicators or market trends to further improve the precision and applicability of sales forecasting models. In conclusion, this research establishes the superiority of the Bayesian Regularization Neural Network (ANN) over the Random Forest model in predicting future sales using past sales data. The findings emphasize the potential value of leveraging advanced AI and ML techniques in sales forecasting and provide a foundation for further advancements in this domain.

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