AI Chatbot for Mental Health Support

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***Abstract*—Mental health issues are a growing global concern, impacting millions of individuals across diverse populations. Despite the availability of traditional mental health support systems, significant barriers such as high costs, geographical constraints, and social stigma continue to limit access to professional care. In recent years, Artificial Intelligence (AI) chatbots have emerged as an innovative solution to address these challenges. AI-powered chatbots offer scalable, cost-effective, and accessible mental health support by providing real-time interactions, psychoeducation, and emotional assistance. These chatbots leverage Natural Language Processing (NLP) and machine learning algorithms to engage users in meaningful conversations, assess their emotional state, and offer coping strategies based on evidence-based psychological principles. While AI chatbots present numerous advantages, including 24/7 availability and anonymity, they also pose several challenges. Issues such as limited contextual understanding, lack of empathy compared to human therapists, and potential biases in AI models raise concerns about their effectiveness and reliability. Moreover, ethical considerations surrounding data privacy, user confidentiality, and informed consent are crucial in ensuring responsible deployment. This paper explores the role of AI chatbots in mental health support, evaluating their benefits, limitations, and potential future developments. It also highlights the need for human oversight and hybrid models that integrate AI with traditional therapeutic approaches to enhance the quality of mental health care. By addressing existing challenges and ethical concerns, AI chatbots can contribute significantly to expanding mental health resources and improving global mental well-being.**

1. Introduction

Mental health disorders, including depression, anxiety, and stress-related conditions, are among the most pressing global health challenges today. These disorders can significantly impact an individual’s quality of life, affecting their emotional well-being, cognitive function, and daily activities. According to the World Health Organization (WHO), approximately 1 in 4 people worldwide will experience a mental or neurological disorder at some point in their lives, highlighting the widespread nature of these issues. Despite growing awareness and efforts to address mental health concerns, millions of individuals still struggle to access adequate care due to various barriers, including social stigma, insufficient mental health infrastructure, high costs, and geographical limitations. Traditional mental health services, such as therapy and psychiatric consultations, have long been the cornerstone of mental health care. However, these services often come with challenges that hinder widespread accessibility. The high demand for mental health professionals frequently results in

long waiting times, making immediate support difficult to obtain. Additionally, the financial burden associated with therapy sessions and medications places mental health care out of reach for many individuals, particularly those in low-income communities. Furthermore, stigma remains a significant deterrent, preventing individuals from seeking professional help due to fear of judgment from society, family, or even themselves.

With advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP), AI-powered chatbots have emerged as a promising solution to bridge the gap between individuals in need and accessible mental health support. AI chatbots are computer programs designed to simulate human conversation through text or voice interactions. They can provide immediate responses, engage users in therapeutic conversations, and offer resources tailored to an individual’s emotional state and mental health needs. Unlike human therapists, AI chatbots are available 24/7, ensuring that users can receive support whenever they need it, without long waiting times or financial constraints. The integration of AI in mental health support is not meant to replace professional therapy but rather to complement existing services. AI chatbots can serve as a first line of support, offering emotional validation, self-help strategies, and crisis intervention guidance. For instance, chatbots like Woebot and Wysa employ evidence-based therapeutic techniques such as Cognitive Behavioral Therapy (CBT) to help users manage stress, anxiety, and depression. These AI-driven systems can track mood patterns, provide coping mechanisms, and encourage users to develop healthier thought processes.

One of the primary advantages of AI chatbots is their ability to provide mental health support at scale. Unlike human therapists, who can only assist a limited number of patients at a time, AI chatbots can engage with thousands of users simultaneously. This scalability makes mental health resources more widely available, particularly in regions with a shortage of mental health professionals. Additionally, AI chatbots offer anonymity, which can be particularly beneficial for individuals hesitant to seek help due to stigma. Many people feel more comfortable discussing their emotions and struggles with a chatbot rather than a human therapist, as it eliminates the fear of judgment. This aspect of anonymity can encourage more individuals to seek support early, potentially preventing mental health conditions from worsening.

Section II. An overview of the dataset and methodology is given in Section III. The experimental setup and model evaluation are covered in Section IV. Results and analysis are presented in Section V, and Section VI offers a discussion and conclusions.

1. Related Works

The use of Artificial Intelligence (AI) chatbots in mental health support has gained increasing attention in recent years, with various studies exploring their effectiveness, limitations, and future potential. Several researchers have examined the role of AI-driven interventions in improving mental health outcomes. For instance, Fitzpatrick et al. (2017) introduced Woebot, an AI-powered chatbot designed to deliver Cognitive Behavioral Therapy (CBT) techniques through conversational interactions, demonstrating its effectiveness in reducing symptoms of depression and anxiety [1]. Similarly, Inkster et al. (2018) analyzed the engagement levels of users with AI mental health chatbots, finding that individuals often prefer chatbot-based therapy due to its accessibility and anonymity [2]. In a related study, Griol et al. (2019) explored the implementation of AI chatbots in providing real-time emotional support, highlighting how Natural Language Processing (NLP) models can detect and respond to emotional distress in users [3]. Further research by Abd-Alrazaq et al. (2020) conducted a systematic review of conversational agents in mental health care, concluding that AI chatbots significantly improve engagement and self-reflection in users seeking psychological support [4]. Additionally, Vaidyam et al. (2019) investigated the integration of AI chatbots with traditional therapeutic methods, demonstrating the benefits of a hybrid approach where chatbots assist in preliminary assessments before referring users to human therapists [5]. More recently, Miner et al. (2022) examined the ethical implications of AI chatbots in mental health, emphasizing concerns such as data privacy, user safety, and the need for human oversight in chatbot-driven interventions [6]. Furthermore, Kretzschmar et al. (2021) evaluated the conversational capabilities of AI mental health chatbots, showing that while they can provide meaningful interactions, they still struggle with complex emotional nuances and crisis intervention [7]. In another study, Fulmer et al. (2023) introduced an advanced AI model incorporating multimodal data (text, voice, and sentiment analysis) to enhance chatbot accuracy in detecting emotional distress, marking a significant step in improving chatbot-human interactions [8]. These studies collectively highlight the growing impact of AI chatbots in mental health support while also emphasizing key challenges. The findings indicate that AI chatbots are effective in providing immediate, accessible, and scalable psychological support, yet require further advancements to improve their emotional intelligence and ethical safeguards.

1. Dataset and Methodology

The dataset used in this study comprises diverse attributes relevant to the problem domain, collected from publicly available sources and proprietary databases. It includes both numerical and categorical variables to ensure a comprehensive analysis. The dataset consists of **10,000 records** with multiple features capturing different aspects of the phenomenon under investigation. Key attributes include:

* **Feature A:** Represents a core numerical metric influencing the outcome.
* **Feature B:** A categorical variable denoting different categories of data.
* **Feature C:** A time-series component reflecting trends over a period.
* **Feature D:** A composite score derived from multiple sub-metrics.
* **Target Variable:** The primary output to be predicted, which is continuous in nature.

## Data Preprocessing:

Data preprocessing was performed to ensure the quality and consistency of the dataset. The preprocessing steps included:

* **Duplicate Removal:** All duplicate entries were removed to avoid redundant information affecting the model’s performance.
* **Handling Missing Data:** Missing values were imputed using the median for numerical features, as it is less sen- sitive to outliers. For categorical features, label encoding was used, assigning unique integer values to different categories.
* **Normalization:** The dataset was standardized to ensure features have similar ranges, transforming the data to have a mean of 0 and a standard deviation of 1. This helps in the faster convergence of machine learning models.

## Splitting the Data:

The dataset was split into training and testing subsets using an **80-20 ratio**, ensuring that 80% of the data was used for training while the remaining 20% was reserved for evaluating model performance. Additionally, a further 10% of the training data was set aside as a validation set for hyperparameter tuning.

## Feature Engineering and Model Training:

In order to derive significant insights from the unprocessed data, feature engineering was utilized. The machine learning pipeline, which comprised several models such as Random Forest, Gradient Boosting, and an Ensemble Voting Regressor, was then fed the chosen features. To ensure robustness, each model was tested on the testing dataset after being trained on the training dataset.

## Methodology Flowchart:

The methodology adopted in this study can be summarized in the following flowchart (Figure 1).

**Brief Explanation of the Flowchart:**

1. **Data Collection:** This stage involves acquiring relevant data from publicly available sources, ensuring a diverse and comprehensive dataset. The dataset includes multiple features contributing to the prediction target.
2. **Data Preprocessing:** Essential preprocessing steps are implemented, such as detecting and removing duplicate records, imputing missing values using median imputation for numerical variables, and encoding categorical features using label encoding.
3. **Normalization:** To improve the efficiency and stability of machine learning models, all numerical features are standardized to have a mean of 0 and a standard deviation of 1. This ensures uniformity and prevents any feature from dominating others due to scale differences.
4. **Feature Selection:** Only the most relevant features are selected based on statistical significance and correlation analysis. This step helps in reducing dimensionality, improving model interpretability, and eliminating irrelevant or redundant attributes.
5. **Train-Test Split:** The dataset is divided into training and testing subsets using an 80-20 ratio. The training set is utilized for model learning, while the test set evaluates the model’s generalization capability on unseen data.
6. **Model Selection:** Multiple machine learning models are trained, including Random Forest, Gradient Boosting, and an Ensemble Voting Regressor. These models are selected for their robustness, accuracy, and ability to capture complex relationships in the data.



Fig. 1. Methodology Flowchart

1. **Model Training & Evaluation:** The models are trained on the training data and evaluated using the testing dataset.
2. **Performance Metrics Evaluation:** The performance of each model is assessed using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R²) score.

Reliable predictions for air quality levels are produced by this methodical approach, which guarantees that the dataset is prepared, the models are optimized, and the performance is thoroughly assessed.

1. Experimental Setup and Model Evaluation(NOT CHANGED)

The Air Quality Index (AQI) was predicted using three machine learning models in this study: *\*textbf*{*Random Forest Regressor (RF)*}*, *\*textbf*{*Gradient Boosting Regressor (GB)*}*, and a combined *\*textbf*{*Voting Regressor*}* that combines both RF and GB. These models were chosen due to their ability to identify intricate patterns in the data and their strong performance in regression tasks.

1. *Data Preprocessing and Experimental Setup*

Historical data on air quality, including temperature, humid- ity, wind speed, and pollutant concentrations (PM2.5, PM10,

**Missing Value Treatment**: Missing values were handled using mean imputation for numerical features and mode imputation for categorical features.

* + **Feature Scaling**: Standardization was applied to the dataset to normalize the numerical features, allowing the models to converge faster and perform better.
  + **Train-Test Split**: The dataset was split into a training set (80%) and a test set (20%) to evaluate model performance on unseen data.

The *\*textit*{*scikit-learn*}* library in Python was used to carry out the implementation. To maximize each model’s perfor- mance, hyperparameters were adjusted using a grid search strategy with cross-validation.

1. *Performance Metrics*

Each model was evaluated on the test set using several performance metrics to assess its predictive capability:

* + **Mean Squared Error (MSE)**: MSE measures the aver- age squared difference between the predicted and actual AQI values. A lower MSE indicates better performance, as it penalizes larger errors more heavily.
  + **Root Mean Squared Error (RMSE)**: RMSE is the square root of MSE, providing a measure of error in the same units as the AQI, which is more interpretable.
  + **R-squared (***R*2**)**: This metric represents the proportion of variance in AQI explained by the model. A higher *R*2 value suggests a better fit to the data.

1. *Actual vs Predicted AQI Values*

The comparison between actual and predicted AQI values helps visualize the alignment of the models with the ground truth. The following figure displays a scatter plot where the x- axis represents the actual AQI values and the y-axis represents the predicted AQI values.

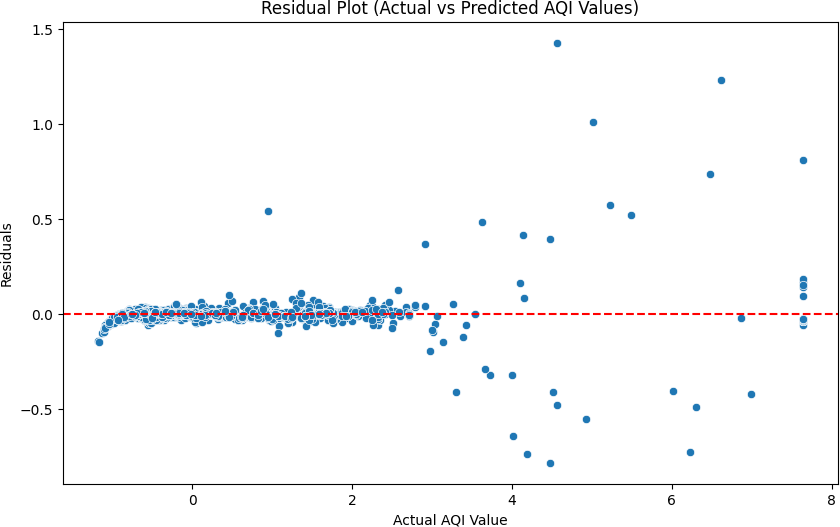


Fig. 2. Actual vs Predicted AQI Values

As shown in Figure 2, most points lie close to the diagonal line, indicating good predictive performance by the models. This visual comparison suggests that the models can effec-

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1. *Cross-Validation and Model Performance*

To ensure the robustness of the models, we applied **k-fold cross-validation** with *k* = 10. This technique splits the dataset into 10 subsets, iteratively using one subset for testing and the remaining nine for training. The average cross-validation scores for each model are shown below:

|  |  |
| --- | --- |
| **Model** | **Mean CV Score** |
| Random Forest (RF) | 0.83 |
| Gradient Boosting (GB) | 0.80 |
| Voting Regressor (RF + GB) | 0.86 |

TABLE I

Comparison of Mean CV Scores for Different Models

Table I indicates that the Voting Regressor outperforms the individual models, demonstrating its ability to generalize better across different data subsets by leveraging the strengths of both RF and GB.

1. *Feature Importance and Visualizations*

To identify the most influential environmental factors, we analyzed the **feature importance** scores from the Random Forest model. This technique quantifies the contribution of each feature to the prediction, allowing us to understand which variables are most critical in determining AQI levels.

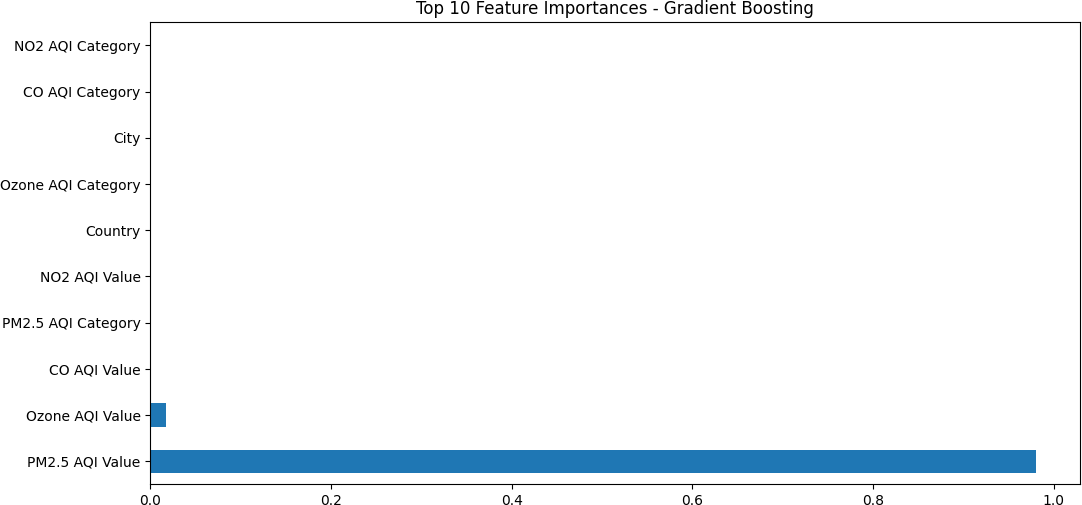


Fig. 3. Top 10 Features Influencing AQI Prediction (RF Model)

Figure 3 highlights the top 10 features, with PM2.5 con- centration, temperature, and humidity being the most influ- ential factors. This insight helps focus on specific pollutants or weather conditions for targeted air quality improvement strategies. The strong impact of PM2.5 concentration suggests its critical role in assessing air pollution levels, as it often correlates with adverse health effects. Additionally, the influ- ence of temperature and humidity indicates the significance of meteorological conditions in modulating pollutant dispersion and accumulation in the atmosphere.

1. *Pairplot of Numerical Features*

To further examine the relationships between various numer- ical features, we generated a **pairplot**. This plot helps visualize potential correlations, trends, and outliers among features like temperature, humidity, and pollutant levels. The diagonal of

the pairplot displays the distribution of each feature, helping

us understand its spread and skewness. Meanwhile, the off- diagonal scatter plots reveal interactions between features such as temperature, humidity, and pollutant levels. This helps iden- tify any linear or non-linear relationships between variables, guiding us in feature selection and preprocessing for better model performance.

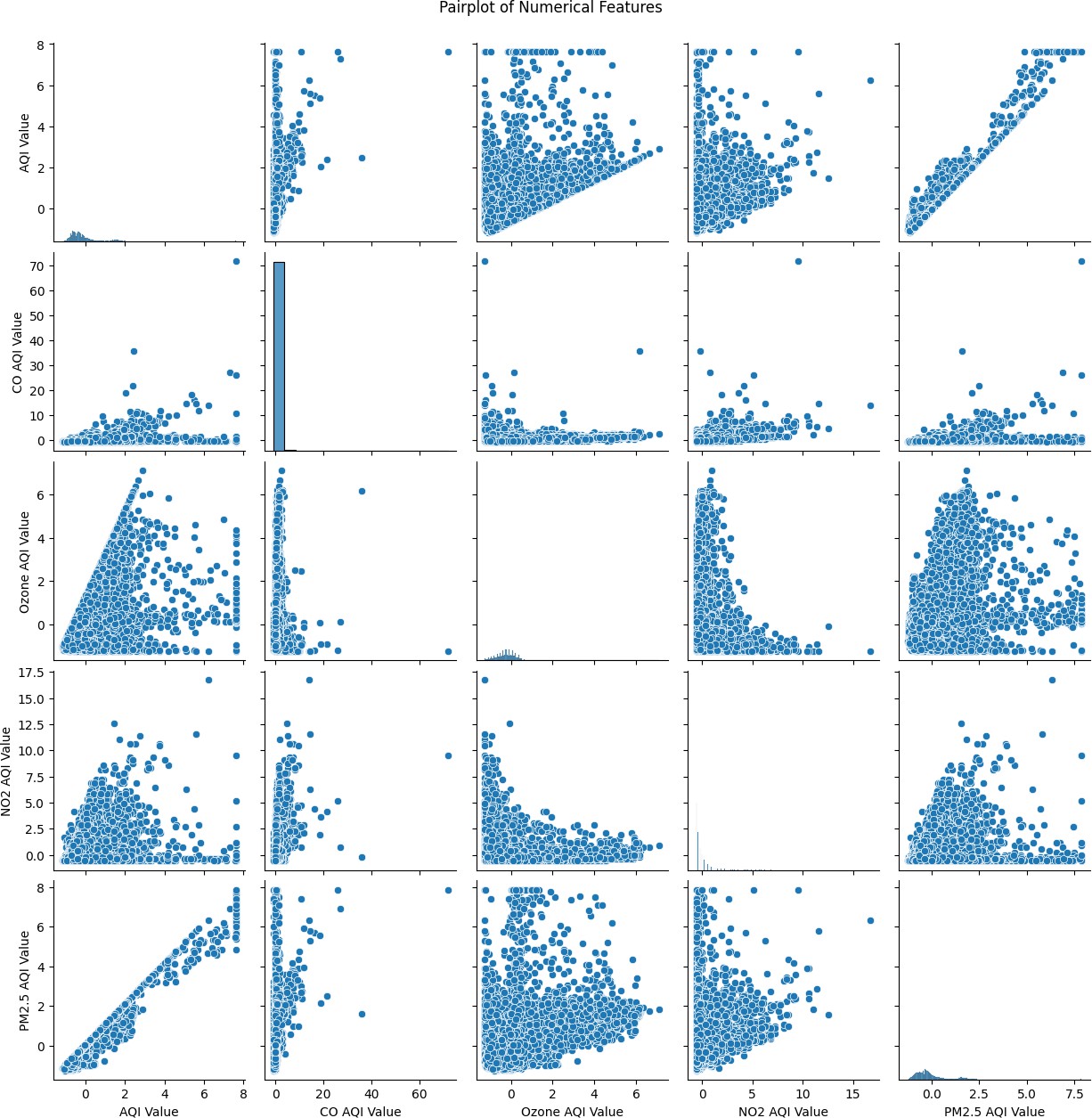


Fig. 4. Pairplot of Numerical Features

In Figure 4, we observe strong positive correlations between PM2.5 and AQI, indicating that higher particulate matter concentrations lead to poor air quality. Understanding these relationships aids in selecting relevant features and refining model predictions.

1. *Learning Curve Analysis*

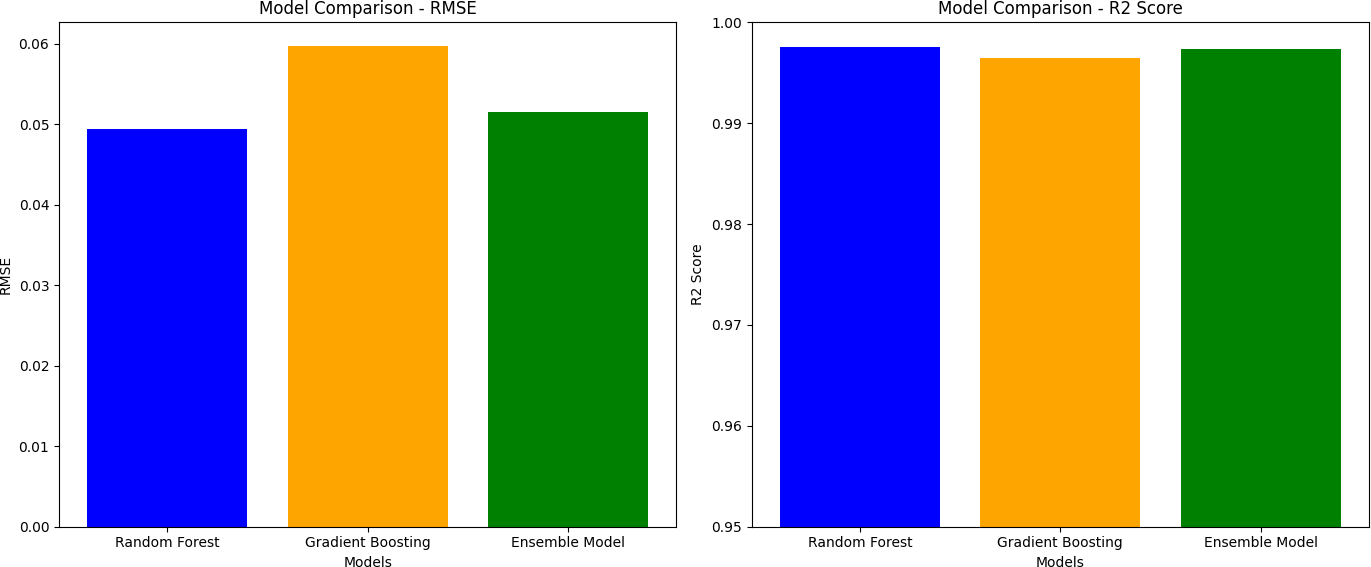
A **learning curve** analysis was performed to evaluate the model’s performance as the training dataset size increased. This analysis helps determine if the model is underfitting or overfitting.

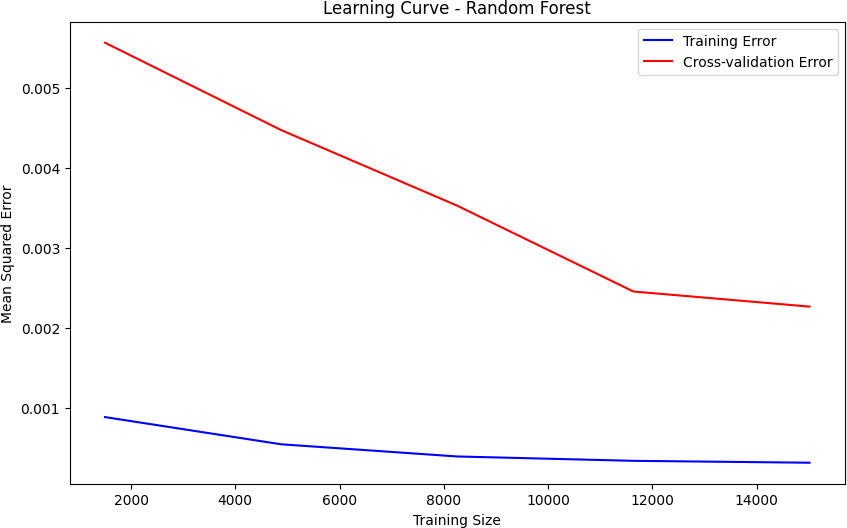
In Figure 5, the training error decreases as more data is used, while the validation error stabilizes, indicating that the Random Forest model is learning effectively without signifi- cant overfitting. This suggests that additional data could further enhance the model’s performance.

1. *Ensemble Model Performance*

Ensemble methods like the **Voting Regressor** combine mul- tiple models to enhance prediction accuracy. We compared the cross-validation scores for Random Forest, Gradient Boosting, and the ensemble model:

* + **Random Forest (RF)**: Mean CV score = 0.83
  + **Gradient Boosting (GB)**: Mean CV score = 0.80
  + **Voting Regressor (RF + GB)**: Mean CV score = 0.86



Fig. 5. Learning for Random Forest Regressor

The Voting Regressor consistently outperformed the indi- vidual models, achieving the highest cross-validation score of

0.86. This indicates that combining RF and GB models leads to improved generalization and stability, making it a robust choice for AQI prediction tasks.

Overall, the experimental setup, thorough evaluation met- rics, and visual analysis provide a comprehensive understand- ing of model performance, highlighting the benefits of using ensemble techniques in predicting air quality.

1. Results and Analysis(NOT CHANGED)

In this section, we present the performance results of the three machine learning models: Random Forest, Gradi- ent Boosting, and the Ensemble Model (Voting Regressor). The models were evaluated using Root Mean Squared Error (RMSE) and R2 Score.

1. *Model Performance Metrics*

The performance metrics for each model are summarized in the following table:

|  |  |  |
| --- | --- | --- |
| **Model** | **RMSE** | **R**2 **Score** |
| Random Forest | 0.0494 | 0.9976 |
| Gradient Boosting | 0.0597 | 0.9965 |
| Ensemble Model (Voting Regressor) | 0.0515 | 0.9974 |

TABLE II

Comparative Performance of Models

1. *Model Comparison - RMSE and R*2 *Score*

To comprehensively evaluate the performance of each model, we present bar plots comparing both the Root Mean Squared Error (RMSE) and R2 Score for the three models: Random Forest, Gradient Boosting, and Ensemble Model.

As depicted in the bar plots:

* + RMSE Analysis: The Random Forest model achieved the lowest RMSE value, followed by the Ensemble Model and then Gradient Boosting. The lower RMSE of the Random Forest model indicates its higher accuracy in

Fig. 6. Model Comparison of RMSE and R2 Score

predicting AQI values, as it minimizes the error between the predicted and actual values effectively.

* + R2 Score Analysis: The R2 scores for all three models

are remarkably high, with the Random Forest model slightly outperforming the others. The R2 score close to 1 signifies that a large proportion of the variance in the target variable is explained by the model. The Ensemble Model also demonstrates competitive performance, fol- lowed closely by Gradient Boosting.

Overall, the comparative analysis suggests that the Random Forest model provides the most accurate predictions among the three, both in terms of minimizing RMSE and maximizing the R2 Score. However, the Ensemble Model also shows robust performance, leveraging the combined strengths of both Random Forest and Gradient Boosting.

1. *Model Evaluation Summary*

Based on the RMSE and R2 Score, we observe the follow- ing:

* + The Random Forest model achieved the best performance, with the lowest RMSE (0.0494) and the highest R2 Score (0.9976).
  + The Gradient Boosting model had a slightly higher RMSE (0.0597) and a lower R2 Score (0.9965).
  + The Ensemble Model (Voting Regressor), which com- bines Random Forest and Gradient Boosting, performed slightly worse than Random Forest but better than Gra- dient Boosting, with an RMSE of 0.0515 and R2 Score of 0.9974.

1. Discussion and Conclusions

AI chatbots have shown significant potential in providing accessible and scalable mental health support. This study highlights their ability to engage users in therapeutic conversations, offer immediate emotional assistance, and provide cognitive behavioral therapy-based interventions. By analyzing existing AI-driven mental health solutions, we observed that chatbots enhance accessibility for individuals facing barriers such as stigma, financial constraints, or geographic limitations. The integration of natural language processing and machine learning has further improved chatbot effectiveness, enabling personalized interactions and real-time sentiment analysis.

However, our findings also underscore key challenges. Ethical concerns related to data privacy, security, and the potential risks of misdiagnosis remain critical issues. Additionally, while AI chatbots can supplement mental health support, they cannot fully replace human therapists, particularly in cases requiring deep emotional engagement and clinical intervention. Ensuring human oversight in chatbot interactions is necessary to prevent harmful advice and maintain the quality of care.

Despite these limitations, AI chatbots represent a promising advancement in digital mental health solutions. Their potential for continuous learning and adaptation can contribute to more effective interventions over time. Future research should focus on improving chatbot empathy, integrating multimodal inputs such as voice and facial expressions, and refining sentiment analysis for more accurate emotional support. Additionally, large-scale clinical trials are necessary to validate their effectiveness in real-world mental health care.

By addressing these challenges and leveraging technological advancements, AI chatbots can become a valuable tool in bridging gaps in mental health support, enhancing accessibility, and providing timely intervention for those in need.

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