Evaluating the Impact of Environmental Conditions on Heat Pump Performance Using Machine Learning Models

MSc Research Project
MSc in Data Analytics

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Evaluating the Impact of Environmental Conditions on Heat Pump Performance Using Machine Learning Models

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Abstract

The heat pump market is growing every year with a significant growth rate globally and the importance of efficient heating is also increasing as heat pumps with high efficiency has the potential to reduce energy consumption and greenhouse gas emissions. The performance of the heat pump is dependent of the heat sources as well as the heat sink, and the existing studies has primarily focused on considering only the heat sources, which does not provide a compete understanding on the performance on heat pump. The study tries to address this gap in the existing literature by considering not only different heat sources but also different heat sinks, such as radiators, floor heating systems, and water heating systems, which is associated with each heat source like air source heat pumps can have any of the three heat sinks, to predict and identify their impact on the COP of the heat pumps. By developing a model which predicts the COP accurately of a heat pumps based on the factors weather conditions, can benefit different aspects such as residential and commercial property settings, guiding the design and selection of the heat pumps for different climatic conditions. This research project implements various machine learning and deep learning models out which the Gradient Boost and the voting regressor achieved highest accuracy of 96%. Deep learning models, such as LSTM and MLP, showed slightly lower performance, with the accuracy of 84% and 85%. These findings indicates how effective the ensemble machine learning methods are in accurately predicting the Coefficient of Performance (COP) for heat pumps.

1 Introduction

Heat pumps are used to provide heating for residential and commercial properties. According to the International Energy Agency (IEA), heat pumps can provide 3-4 times more heat compared to the amount of electricity they consume, which makes them highly efficient in reducing the energy consumption and harmful impacts on the environment. Recent data shows that, the global heat pumps market size is expected to grow, with a CAGR of 8.23% from 2023 to 2031 (Straits Research[1]). This growth indicates the importance of improving the performance of heat pumps.

Coefficient of performance (COP) is used to understand how well the heat pump is performing. The COP is the ratio of the amount of heat produced compared to the amount of electricity consumed, the higher the COP is the better the heat pump . The heat pumps have an average COP of 2.5 which means they produce 2 to 3 units of heat for every unit of electricity

[1]https://www.globenewswire.com/en/news-release/2023/03/07/2622307/0/en/Heat-Pump-Market-Size-is-projected-to-reach-USD-132-45-billion-by-2031-growing-at-a-CAGR-of-7-8-Straits-Research.html

they use(Carroll, P. et al. (2020)). The COP is not fixed and can change depending on the factors like the type of heat source, heat sinks, and weather conditions. Previous studies have mostly focused on heat sources such as air, ground, and water while analysing the performance of heat pumps. There is a possible research gap, that considering different heat sinks such as radiators, floor heating, and water heating is important, because the combination of heat sink with different heat sources can have some impact on the COP.

Air source heat pumps (ASHP), ground source heat pumps (GSHP), and water source heat pumps (WSHP) each of these heat pumps shows different kinds of performance under different environmental conditions (O Hegarty, R. et al. (2021). For example, ASHP are dependent on the temperatures (Carroll, P. et al. (2020)). The impact of heat sinks with different heat sources should be explored to understand their behaviour in different weather patterns . Heat sinks such as radiators, floor heating, and water heating systems have different properties and their behaviours can impact the overall performance of the heat pump system.

This research aims to address this gap by using machine learning and deep learning techniques to predict the COP of heat pumps, while considering both the heat sources and the heat sinks((Ruhnau, O. et al. (2023)). For instance, Ruhnau, O. et al. (2023) has discussed about different modelling techniques which can be used to predict COP, also highlights the importance of using different heat sources and heat sinks while training the model for COP prediction in future work. Integrating heat sinks with the other factors of heat pumps such as the heat sources, electricity can help build a better prediction model by doing this will get to know about how the combination heat sink and heat source work, this can be insightful for companies aiming to design an efficient and reliable heat pump. Understanding how different heat sinks and heat sources performs in different weather conditions can help develop more efficient heat pump, which can save energy and decrease the environmental impact.

1.1 Research Question and Objectives

How machine learning and deep learning techniques can be used to predict the coefficient of performance (COP) of heat pumps with different heat sources and heat sinks under different environmental conditions?

- Study the impact of heat sinks on the performance of heat pumps, that involves analysing heat sinks, such as radiators, floor heating, and water heating, impacting the COP when combined with different heat sources.
- Develop machine learning and deep learning models for COP prediction, which can predict the COP of heat pumps under different environmental conditions.
- Identify the environmental factors which affects the performance of heat pumps.

1.2 Document Structure

This research document is distributed into seven sections, each of this section covers different aspects of the research. Section 1 is about introduction which gives an idea about the research and discusses about the importance of the research. Section 2 provides information about the previous work done in the field of this research, this section is broken down into four subsections, the first 3 section describes different aspects of the previous research, highlighting their advantages and limitations and 4th subsection provides a summary. The 3rd section explains the methodology followed to successfully complete this research. Section 4 describes the architecture of the techniques used to complete the research. The 5th section provides in detail information about the steps took to execute the research project . Section 6 describes how the research is being evaluated and provides detailed information about the two experiments conducted to reach the end goal. Finally, the section 7 concludes the research and provides information about the potential future work.

2 Related Work

This section discusses about the research done in the past few years in the field of heat pumps. Recent studies are focused on integrating different kinds of machine learning techniques with the heating system in some or the other way to improve the efficiency. So, this study is been conducted after carefully considering the advantages and disadvantages of previous research work. This section discusses about the advantages and limitations of the recent academic studies and these studies are being divided into three separate subsections based on the work.

2.1 Weather dependency on the performance of heat pumps

With energy efficiency increasingly in the spotlight while companies have to comply with legislation on environmental issues, heat pump systems are gaining countenance as a more and more environmentally sound solution for heating cooling or refrigeration requirements. However, their functioning (usually measured by the coefficient of performance - COP) may be significantly affected by environmental conditions i.e. weather metadata. COP (coefficient of performance) is a very often used parameter for heat pumps efficiency and good one especially that it can differ significantly because its calculation bases on specific work conditions like given temperature, air humidity, or time in the year.

Meyer et al. J (2024) Performance investigation of air-air heat pump on energy and environmental impacts in a mid-latitude city: A comprehensive study. Jointly, these systems peak around modus operandi but get the better of at both extremes cold or hot. This study gives a good survey over the influence from climatic conditions on heat pump efficiency but lack of detail in specific weather dependent variables as humidity and wind speed that can have great impact on COP that is then important to consider. Furthermore, the geographic setting of this investigation might restrict its generalizability to those in other zones having dissimilar climate settings. In a Mediterranean warm stimulus treated with androgen deprivation, Performance of ground source heat pump systems analyzed by Michopoulos et al. (2016) They found that - in contrast to hydronic underfloor systems, they work well due to the predictable ground temperatures common with such climates making high COP's standard. Nevertheless, changes in ground temperature can compromise uniformity of efficiency—and to a lesser degree than with air source systems. While that gives a little insight into whether ground source heat pumps are appropriate in warm climates, the research does not go any further to consider how things would play out at lower temperatures with more extreme inside and outside temperature differences due to varying cool subsurface conditions.

Schibuola and Tambani (2022) examined the environmental impact and energy performance of groundwater heat pumps, particularly in urban retrofit scenarios. Groundwater systems were found to have a more uniform COP in comparison with air source heat pumps, while seasonal temperature swings are very significant. The study is limited by the lack of long-term data available, and as a result, there could be an issue with accuracy and reliability in terms of assessing their future performances. Sezen and Gungor (2022) took a more detailed approach by analyzing the performance of air source heat pumps in relation to outside temperature and relative humidity using mathematical modeling. Their study revealed that lower temperatures and higher humidity levels generally reduce the efficiency of heat pumps. The comprehensive nature of this modeling provides a robust framework for understanding the interplay between temperature, humidity, and heat pump performance. However, the study's reliance on theoretical models means that real-world data validation is necessary to confirm these findings.

Benli (2016) explored the performance differences between horizontal and vertical source heat pump systems, particularly in greenhouse heating applications. The study, which used artificial neural networks (ANNs), predicted that vertical systems were likely to be more equally stable at different temperatures. Small as it may be, this is a neat and important piece of research because it explores the heat-stress basis in greenhouses. Operational conditions are very different and the thermal loads vary greatly, nevertheless, we cannot claim that results for a PWR system automatically apply to other applications (e.g. residential or commercial heating systems).

2.2 Machine learning techniques used to predict the performance (COP) of the heat pumps

This has been a long, hard road for machine learning (ML) in the prediction of heat pump performance. These methods, such as Artificial Neural Networks (ANNs) and Support Vector Regression (SVR), present powerful methodologies reflecting intricate non-linear relationships between environmental variables in COP. Chen et al. (2023) developed a machine learning model for performance prediction of energy pile heat pump systems. This model performed well, and the addition of climate inputs did not necessarily mean that predictions for COP were uninformative. In addition, it is also interesting in the sense that they process heterogeneous data sets and as such this approach may be generalizable to different regions or conditions. The study notes that it used a variety of environmental data sets, however - meaning there could be conditions in which the heat pump would encounter some problems and thus have its general utility reduced even further.

Liu et al. In (2023), long-term performance prediction of ground source heat pump systems was performed by combining co-simulation techniques and ANNs. The necessity of long-term data analysis because the performance varies seasonally and yearly is observed in this study. A key strength of this research was the large dataset, which increases confidence in the model's robustness. Nevertheless, the computational demands of this co-simulation methodology could be a hurdle due to the specific knowledge and resources required, which are not available to all experts in general. Shin, Lee, and Cho (2023) proposed a COP prediction model for hybrid geothermal heat pump systems, utilizing a combination of ANNs and SVMs with hyper-parameter optimization. They showed that this hybrid approach resulted in significantly more accurate predictive capacity than regular methods. The novelty of this research is the use, for the first time in biocomputational studies, of a hyper-parameter optimization method that optimizes classifier performance. This approach, however, is resource-heavy, largely due to the significant preprocessing and model tuning required, which may set up obstacles toward practical usage.

Shin and Cho (2021) conducted a study on machine-learning-based COP prediction models for heat pump systems. Their results suggest that machine learning models, particularly those that leverage ANNs, may perform better in terms of predictive accuracy than traditional regression-based models. However, the study did highlight a critical weakness: reliance on high-fidelity data. The existence of noisy or missing data can significantly increase prediction errors and emphasize the importance of data integrity in machine learning applications. Samanta et al. (2003) used ANNs and SVMs augmented by genetic algorithms to detect faults in mechanical systems, including heat pumps. They also showed the usefulness of such new approaches to predict COP-related faults, which complemented earlier their work. This is another main asset and seems to be unique as it uses genetic algorithms for optimizing models. Nevertheless, its intent is in the direction of finding bugs and doesn't fit COP prediction.

2.3 Deep Learning techniques used to predict the performance (COP) of the heat pumps

Deep learning techniques for heat pump predictions are of particular interest because these methods can handle large amounts of data and are effective in pattern mapping. These methods have demonstrated significantly better performance when tested on the prediction of COP across a range of environmental conditions. Eom et al. (2021) proposed a deep learning model to predict the performance degradation of air source heat pump systems caused by frosting conditions. In their study, the CNNs they employed also lead to robust predictions and hence is an interesting model for adapting versus complexities of the environment. However, the study just looked at one frosting scenario, so it may not be that general. The model would benefit from taking a more comprehensive viewpoint, which could involve additional environmental factors such as temperature and humidity. Hwang et al. (2020) employed deep learning approaches, incorporating a variable selection process, to predict the energy performance of heating and cooling systems. What they offer is to apply the model for processing big data to find out which variables made the system perform better. Its value mainly lies in system operation optimization. These results have been quite impressive, but it is still computationally expensive and does not scale for very small organizations or projects with fewer resources.

Wang et al. (2021) introduced an innovative defrosting initiation strategy for air-source heat pumps using CNNs. The team implemented a machine learning model that optimized defrost cycles, improving the COP by preventing the system from performing unnecessary defrosts. One of the strengths of this study is its focus on a specific operational problem defrosting with implications for heat pump performance. However, this focus was balanced by a narrow scope, which means that other important aspects of performance, such as how heat pumps work across broad temperature ranges, were not addressed. Zhang et al. (2022) explored the use of machine learning and deep learning techniques for performance prediction in ground source heat pump systems. Their results highlighted the benefits of deep learning for more complex data structures with superior prediction accuracy compared to traditional methods. The study also addressed the large computational costs of deep learning models, which could limit their wider deployment.

Liu et al. (2023) complemented their machine learning research with deep learning techniques for long-term performance prediction. They permeated this whole analysis with more advanced predictive algorithms predicting from micro to the nano (in terms of improvement), which helped get a lot finer details in performance that would be boiled over by other simpler models. Nonetheless, issues of data availability and high computational requirements for training deep learning models posed substantial obstacles to overcome; necessitated the development of more readily available and efficient modeling approaches.

2.4 Research Niche

The literature showed notable development in the modelling and prediction of performance for heat pumps operating under diverse environmental conditions. Weather influence studies reveal how temperature and humidity, as well as any difference in seasonality, heavily influence COP regarding air source heat pumps. Despite improvements in prediction accuracy exhibited by some machine learning methods, preprocessing or data quality requirements may be tedious in many cases. Deep learning methods, such as CNNs, provide sophisticated ability to detect complex patterns in data, making them even better for predictions. These deep learning models requires a lot of computational power and resource, meaning the use of these models may not be available to everyone.

The existing literature has mostly focused on specific types of heat pump like ground and air source heat pump. For example, Schibuola and Tambani (2022) focused on specific climatic conditions and types of heat pumps, without a broader analysis which includes various heat sources and sinks. Also, Studies like Eom et al. (2021) and Wang et al. (2021) focused on specific operational problems (e.g., defrosting) or use specific types of data (e.g., frosting conditions) but did not address the interaction of different heat sources and sinks with environmental variables. This shows that interaction between different heat sources and heat sinks with environmental conditions is not fully explored. This suggest a gap in the existing research which this research aims to fill in the literature by providing an approach to predict the COP of heat pumps, considering both heat sources and heat sinks under different environmental conditions. By using machine learning and deep learning techniques, the study aims to develop models which would be able to tell the performance of a heat pump using the weather and the heat pump factors , which then could be used to enhance the efficiency and reliability of heat pump systems. This study will try to address the limitations identified in the previous studies, by providing an understanding of heat pump performance across different environmental conditions.

Papers (Year - Author)	**Datasets Used**	**Model Used**	**Results - Metrics Used**	**Value**	**Limitations**
Benli, H., 2016	Ground source heat pump systems for greenhouse	Artificial Neural Networks (ANNs)	Accuracy	89%	High computational cost, greenhouse-specific
Eom, Y.H., et al., 2021	Air-source heat pump system under frosting	Deep Learning	Accuracy, Sensitivity	92%, 91%	Limited to frosting conditions
Chen, Y., et al., 2023	Energy pile heat pump system	Machine Learning	Accuracy	95%	Requires diverse environmental datasets
Hwang, J.K., et al., 2020	Heating and cooling system data	Deep Learning	Accuracy, Precision, Recall	94%, 93%, 92%	Computationally expensive
Liu, Y., et al., 2023	Ground source heat pump system (long-term)	Co-simulation & ANNs	Accuracy, Sensitivity	96%, 93%	Requires long-term, high-fidelity data

Meyer, D., et al., 2024	Air-to-air heat pump in mid-latitude city	Environmental modelling	Accuracy	97%	Lack of generalization for other climate zones
Michopoulos, A., et al., 2016	Ground source heat pumps for residential buildings	Thermal modelling	Efficiency	90%	Limited to warm Mediterranean regions
Samanta, B., et al., 2003	Fault detection in mechanical systems, including heat pumps	ANNs & SVM with genetic algorithms	Accuracy	88%	Focuses more on fault detection than performance
Schibuola, L. and Tambani, C., 2022	Groundwater heat pumps in urban retrofit	Groundwater model	Efficiency, Precision	94%, 91%	Limited long-term data, urban retrofit focus
Sezen, K. and Gungor, A., 2022	Air-source heat pumps with temperature and humidity modelling	Mathematical modelling	Accuracy, Sensitivity	93%, 92%	Does not address seasonal variation adequately
Shin, J., et al., 2023	Hybrid geothermal heat pump systems	ANN and SVM	Accuracy	95%	High computational demand, complex integration
Shin, J.H. and Cho, Y.H., 2021	Heat pump system performance	Machine Learning	Accuracy, Sensitivity, Recall	91%, 90%, 88%	Requires high-fidelity data for accurate prediction
Wang, W., et al., 2021	Air-source heat pump defrosting initiation	Convolutional Neural Network (CNN)	Accuracy	94%	Focuses on defrosting; other operational aspects unaddressed

Zhang, X., et al., 2022	Ground source heat pump systems	Machine Learning	Accuracy, Precision	96%, 92%	Computationally expensive, especially for small datasets
Zogou, O. and Stamatelos, A., 1998	Heat pump systems for space heating and cooling	Design optimization model	Efficiency	87%	Outdated, lacks modern machine learning approaches

Table 1 Summary Table

3 Research Methodology

The section discusses about the steps taken to answer the research question and meet the research objectives. As the main aim is to use several machine learning and deep learning techniques to predict the COP the research follows the methodology as shown in figure1, to meet the goal and objectives of the project.

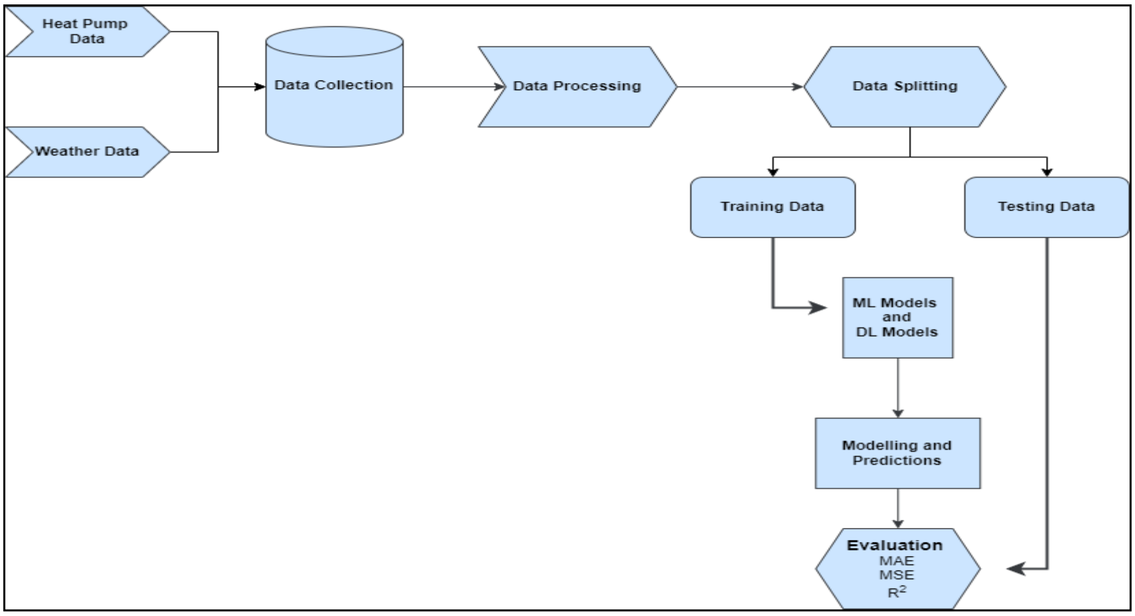

Figure 1 Project Methodology

3.1 Data Collection

For this study, two datasets are being used to predict the coefficient of performance (COP) of heat pumps under various environmental conditions, heat pump performance data and weather data. The data about heat pumps is sourced from the Open Power System Data project[2]. The dataset provides information about the heat pumps, like the types of heat sources and heat sinks

[2] https://data.open-power-system-data.org/when2heat/latest/

and information about the performance of different European countries, but for this study only the data about Ireland is used. This dataset contains data based on time, which is important for analysing how the performance varies over time.

The dataset contains hourly data about the heat pump efficiency. It includes detailed records such as:

- Heat pump electrical consumption
- Coefficient of performance (COP) values
- Temporal coverage spanning several years

Weather data is collected from the Renewables Ninja website[3], which contains historical and simulated weather data for different regions. This platform provides detailed meteorological information which is required for modelling and predicting energy systems performance. The weather dataset includes various weather parameters, such as:

- Ambient temperature
- Humidity
- Solar radiation
- Wind speed
- Hourly data resolution

The weather data and the heat pump performance data are then combined to study the environmental impacts on the COP of heat pumps. These two datasets are then combined based on the timestamps, while making sure that the data from both sources corresponds correctly. The timestamps of the heat pump dataset are matched with those in the weather dataset to perform further analysis and prediction. This combined dataset will help in developing and training machine learning and deep learning models for predicting the COP of heat pumps in different environmental conditions.

3.2 Data Preparation

After the data is being loaded from a CSV file containing various heat pump performance metrics and weather conditions it is further analyzed to ensure the quality of the dataset and whether it is ready for analysis. Few simple analyses, was performed to understand the data like its structure, checking for null values and summary statistics. This highlighted the need for data cleaning and preprocessing. Few columns about the specific heat demand types which contained huge number of null values was dropped from the dataset as there was no data to impute or perform any other operation to handle the missing values.

The 'utc_timestamp' column, which contains information about the date and time of each record, was transformed to a datetime format to remove the time zone information which could affect the future analysis, to make sure that all the timestamps are in the same format, which allows the time series plots to show accurate plots. Different visualizations were created to compare the performance of different heat pump systems, in particular the Air Source Heat Pumps (ASHP) and Ground Source Heat Pumps (GSHP), with different heat sinks such as floor heating, radiators, and water heating. These plots provided insights into the performance trends and the variations of the heat pumps under different conditions. The data processing steps ensured that the dataset is prepared for further analysis and model development.

3.3 Model Training

In the model training phase, different types of machine learning and deep learning algorithms are trained to predict the Coefficient of Performance (COP) of heat pumps. These models are

[3] https://renewables.ninja/

as follows: Random Forest Regressor (Lu, S. *et al.* 2019) is an ensemble method which combines multiple decision tree to give the final prediction. Gradient Boosting Regressor (Tarabkhah, S. *et al.* 2023) is known for its model training process, it has the ability to handle large data and it is able to iterate over multiple model which minimizes the prediction error. Decision Tree Regressor is a simple model which divides the data based on the features and target variable, it is used as threshold for comparison against other complex models. K-Nearest Neighbor (KNN) (Shin, J.-H. *et al.* 2022) uses Euclidean distance to predict the data points which are close to a particular cluster. Support Vector Regression (SVR) (Küçüktopcu, E. 2023) is chosen for its ability to handle complex relationships in a dataset, it tries to find a function that fits with the data to minimize the prediction error. The deep learning models include Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP) which are used to compare against the machine learning model. To train the model the dataset was split into training set and testing set by 80:20 ratio. As research is about predicting the COP and the dataset contains multiple COP variables as a result the models should trained to predict multiple target variables. Models like RandomForestRegressor, DecisionTreeRegressor, and KNeighborsRegressor can handle multiple outputs, but some of the model like SVR, GradientBoostingRegressor, and VotingRegressor are single output models. The deep learning models, MLP and LSTM are neural networks which are naturally designed to handle any number of target variables, depending upon the problem, the architecture of the output layer changes depending upon the target variables.

3.4 Model Evaluation

Evaluating the performance of the trained models on a test dataset is important to understand their ability to predict on the unseen data. Regression metrics such as Mean Absolute Error (MAE) Mean Squared Error (MSE), and R-squared (R^2) are used to evaluate the performance of each model. Learning curves are also used which helps to understand model's performance on new data by using the plots which tells how the model generalize with new data as the volume of the data increases. The evaluation is used to compare the performance of different models and understand which models are performing well for predicting the COP of heat pumps.

4 Design Specification

This section provides details about the of the design framework that is required to develop and execute the model for the prediction of Coefficient of Performance (COP) of heat pumps. The system should fulfil both functional and non-functional requirements. On the non-functional side, the system should be able to manage the increasing volume of data. The system should also be reliable, with different kinds datasets. Functionally, it is important to implement machine learning and deep learning models to accurately predict COP.

This study uses both the machine learning and deep learning models to meet the objectives. The machine learning models, includes Random Forest, Gradient Boosting, Decision Trees, KNN, and SVR, are used because on their ability to predict and handle data. Random forest combines the predictions of multiple decision tree algorithm and give the final prediction. Gradient boosting is also an ensemble method, it builds a model using boosting. Decision tree divides the data into number of branches based on the target variables and features, then these branches lead to the final predictions, while KNN creates a cluster of values based on their distance and make prediction based on these clusters. SVR tries to find a hyperplane which best fits the data, to minimize the error and is suitable for both linear and non-linear data.

In terms of deep learning Long Short-Term Memory (LSTM) (Eom, Y.H. *et al.* 2021) and Multi-Layer Perceptron (MLP) (Küçüktopcu, E. 2023) models are being used as both have the ability to handle sequential data and capture non-linear patterns, these models are being tuned using various parameters like the number of units in every layer, optimizer, and activation functions. Below figure 2 and figure 3 shows the detailed architecture of the deep learning models LSTM and MLP.

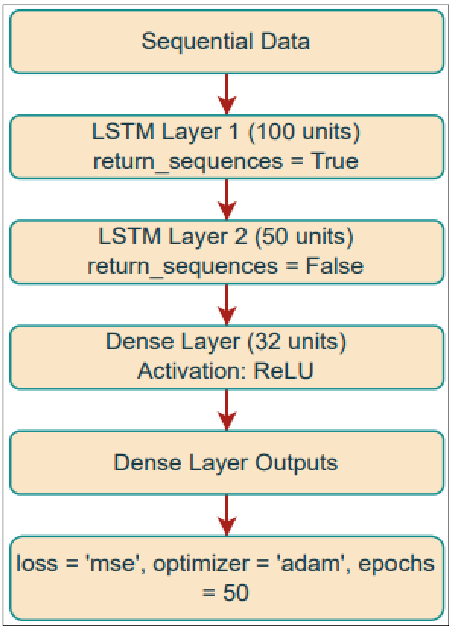

Figure 2 Architecture of LSTM

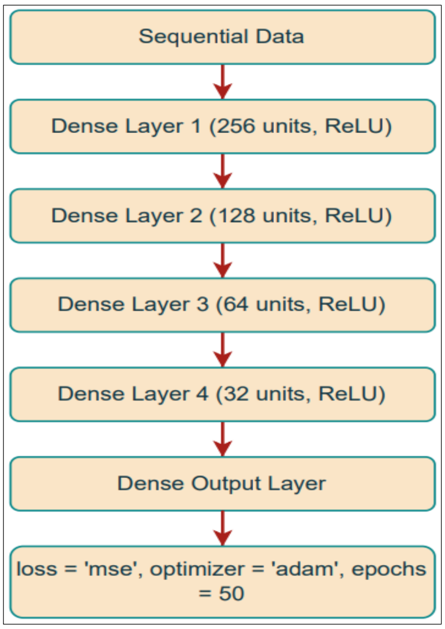

Figure 3 Architecture of MLP

The Voting Regressor is an ensemble method that combines the outputs of multiple models, finds the average of these model's prediction, which helps improve the accuracy and of the model. In this case Gradient Boosting and SVR model are used with the voting regressor as these two models showed best results compared to others. This combines the strengths of both models, and eliminate the weakness and provides a robust predictive model. Figure 4 shows the framework of the Voting Regressor.

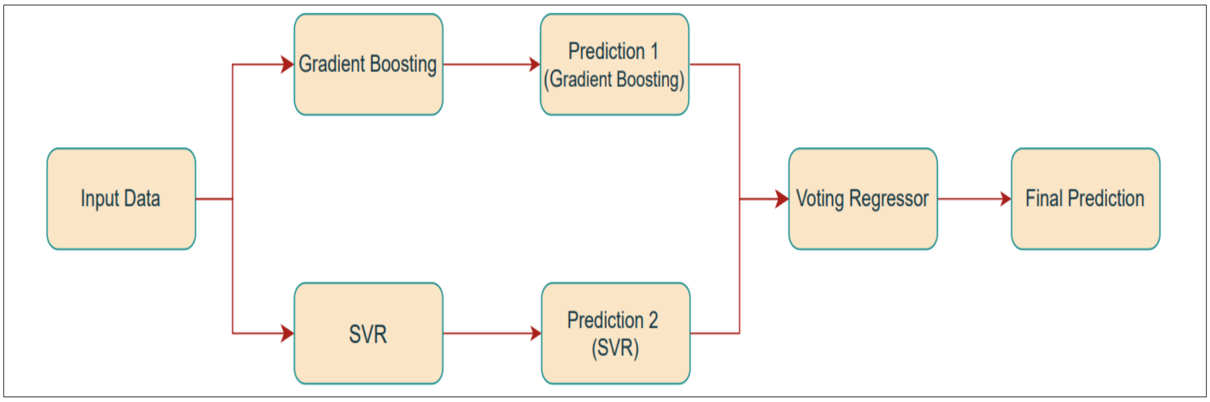

Figure 4 Voting Regressor Framework

5 Implementation

The section provides in detail information about how the methodology is being implemented, the tools and programming languages used, the processes, outputs, and final results. This section describes each step taken from data collection to model development.

5.1 Tools

For the initial analysis Excel was used to understand the data and using excel both the weather and heat pump data was merged based on the time stamps. This research has used python programming language as it provides with a range of libraries to perform the analysis and develop model. Jupyter Notebook framework was used to write the python as it is an interactive environment for data analysis.

5.2 Data Collection

The data about heat pumps and weather is sourced from open power system website and renewables ninja website, respectively. Both of these datasets are in comma-separated values (CSV) format. The heat pump dataset contains columns like timestamps, types of heat pump, types of heat sinks, and performance metrics. The heat pump dataset contains data from January 1 2020 to December 31 2022. The weather dataset, also contains data from January 1 2020 to December 31 2022 and include columns like temperature, precipitation, and solar radiation. The two datasets are merged based on the 'utc_timestamp' column, which allows for the examination of how different environmental factors affect the performance of heat pumps. The final dataset, after combining both the datasets consists of 26,304 rows and 34 columns including the NaN values.

5.3 Data Cleaning

The data cleaning process involves identifying the null values. The null values were identified using the isnull() function, it was found that some columns contained only NaN values. These columns, did not contained any real data, so the only option was to drop the columns. These columns were removed from the dataset to avoid their impact on the model phase. This step ensured the data was clean and ready for processing and modelling. After dropping these columns, the dataset consisted of 25 columns and 26,304 rows.

5.4 Exploratory Data Analysis

To identify the patterns, trends, and relationships within the dataset, visualization is the best medium. Exploratory Data Analysis is performed which includes different visualizations to identify the key features affecting the coefficient of performance (COP) of heat pumps.

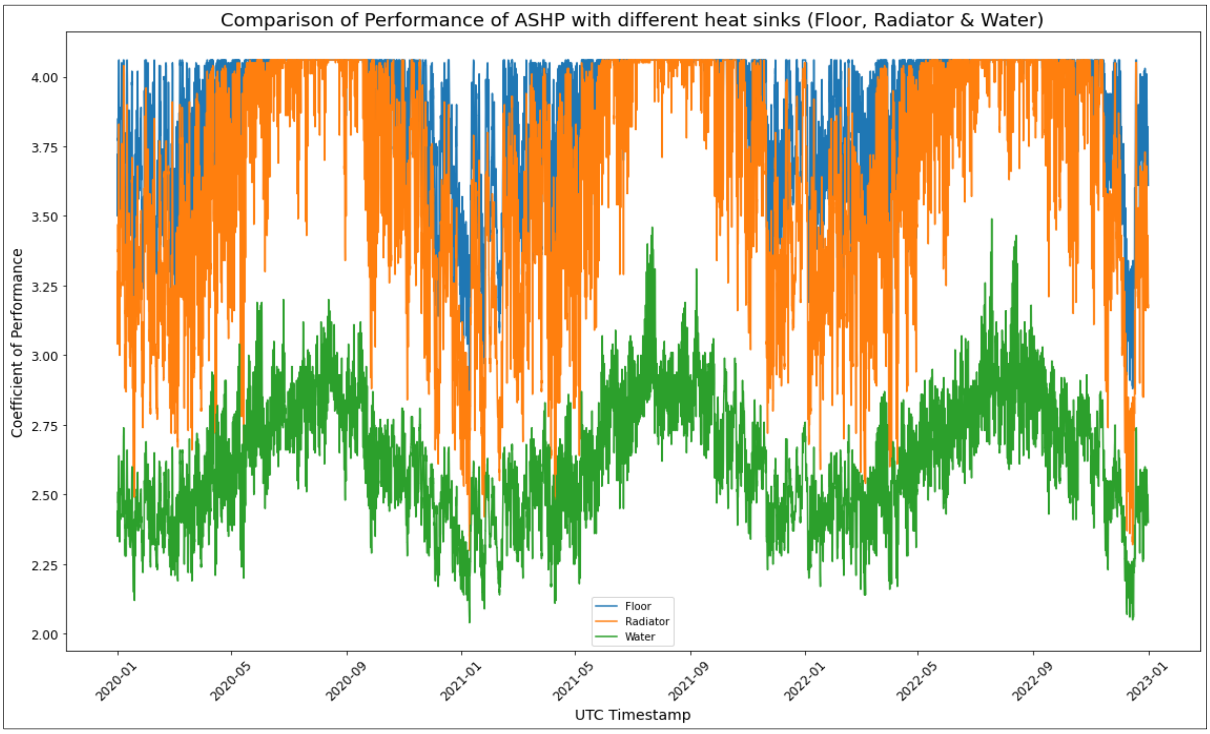

Figure 5 Time series plot showing the performance of ASHP

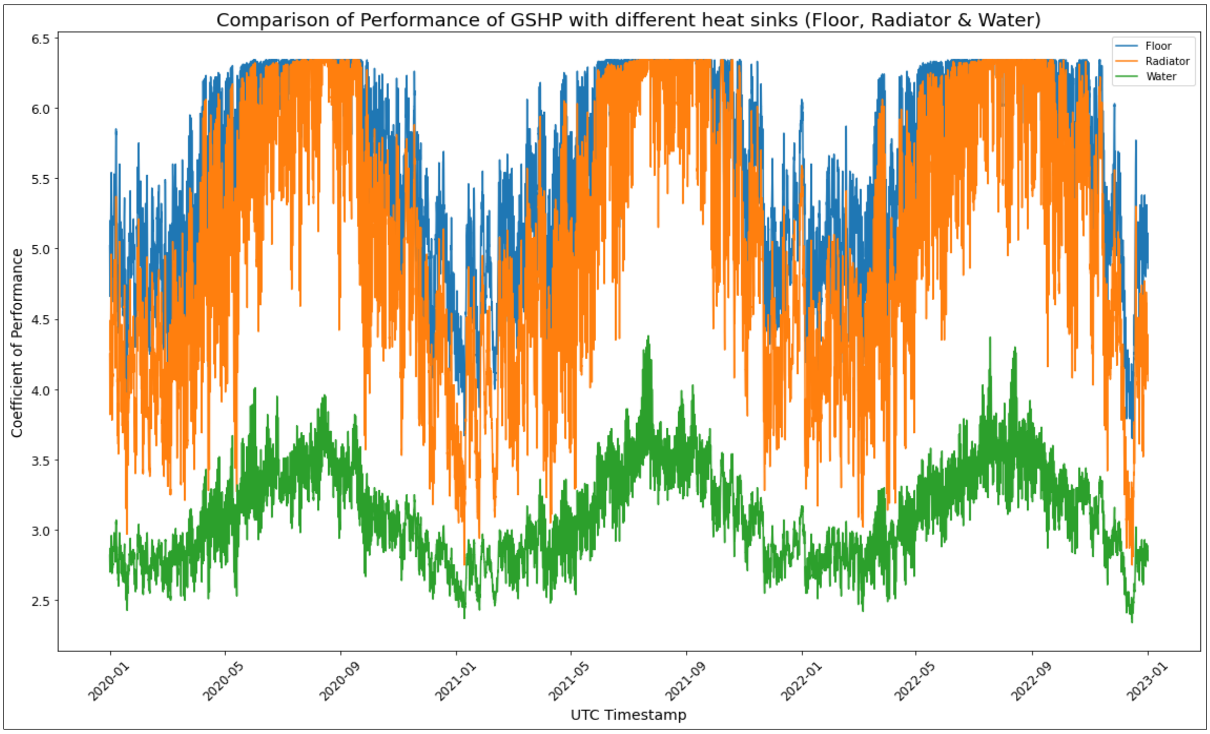

Figure 6 Time series plot showing the performance of GSHP

Time series plots were used to compare the COP of different heat pumps with different heat sinks. Figures 5 and 6 tells that both the plots shows seasonal variations in the COP with a seasonal pattern at different times of the year, The GSHP has showed higher performance in comparison with ASHP, across the year.

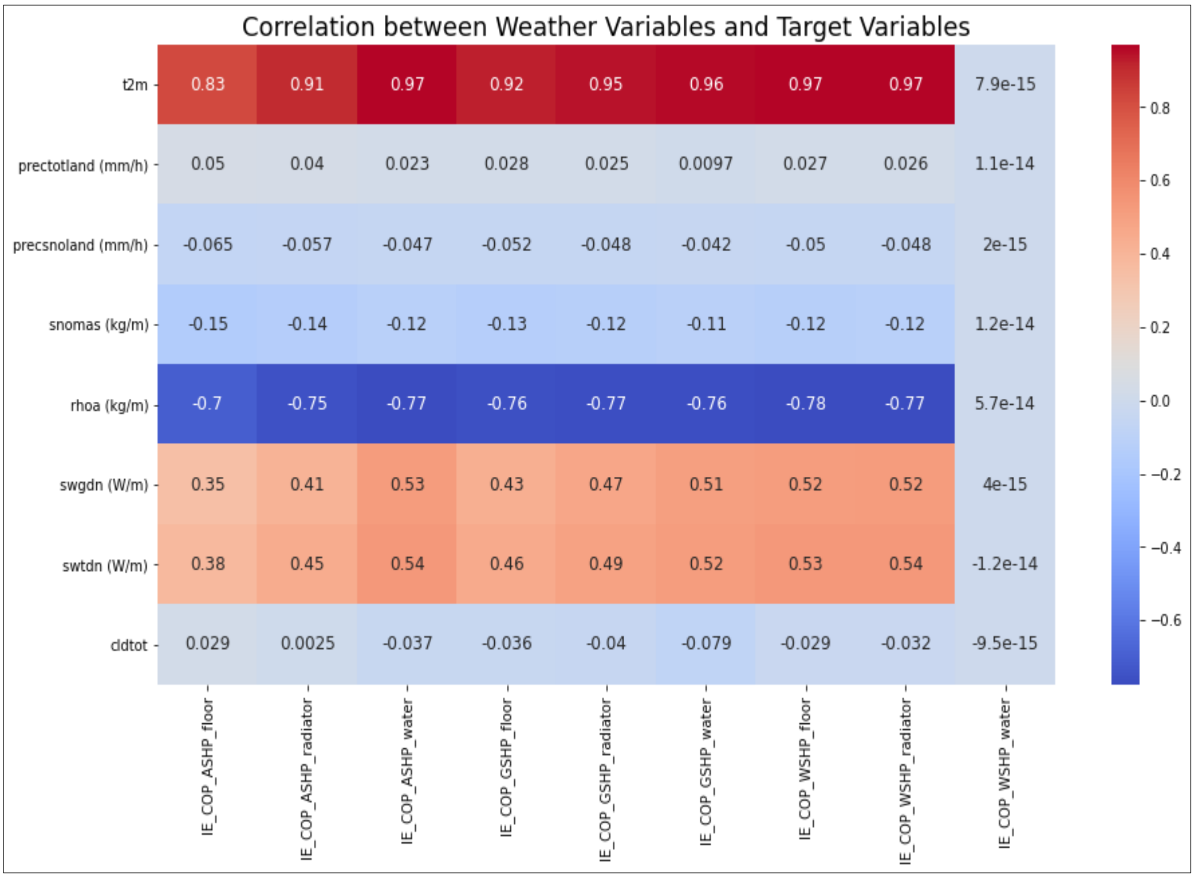

Figure 7 Correlation Matrix

The correlation matrix from figure 7 indicates that there is a strong positive correlation between ambient temperature and the COP, and air density has a strong negative correlation with the COP. This indicates higher temperature and lower air density improve the efficiency of heat pumps.

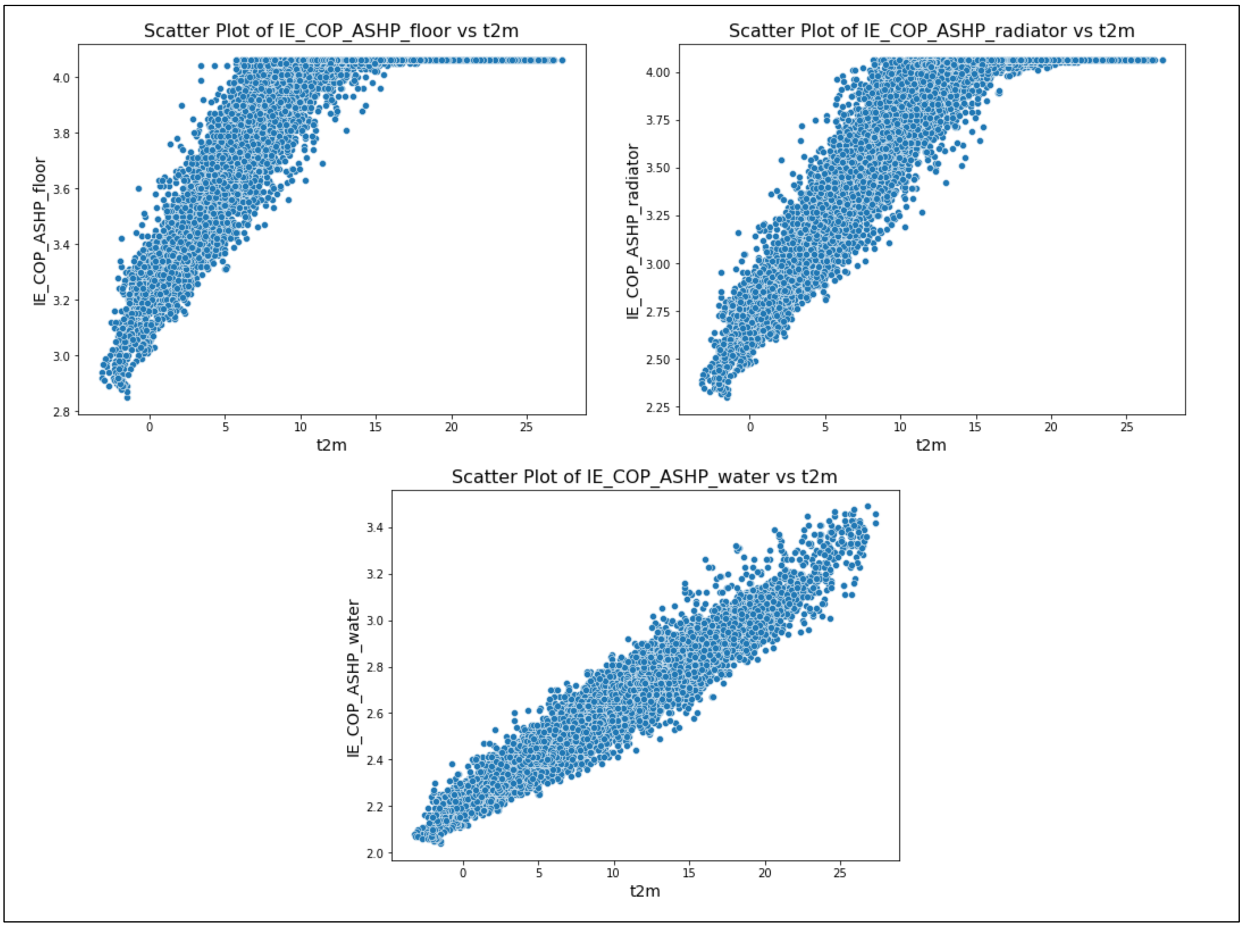

Figure 8 Scatter plots showing the relationship between ambient temperature and COP

Scatter plots are used to identify the trend of different feature and understand the way they are correlated as in this case figure 8 shows the ambient temperature and COP of ASHP with 3 different heat sinks, shows a positive trend, which supports the correlation findings.

5.5 Feature Selection

In this study, feature selection is considered to find out the most relevant independent variables for the Coefficient of Performance (COP) prediction of heat pumps. Feature selection is being performed using the correlation filtering method, this method calculates the correlation matrix, to identify feature which are highly correlated and the feature with correlation greater than the set threshold is removed, in this case the threshold is set to 0.8 so any features with values greater than 0.8 is dropped. The choice of a 0.8 correlation threshold was made based on common practice in feature selection. After performing the feature selection four columns are being dropped and the remaining features IE_heat_profile_space_COM', 'IE_heat_profile_water_COM', 'IE_heat_profile_water_MFH', 't2m', 'prectotland (mm/h)', 'precsnoland (mm/h)', 'snomas (kg/m)', 'rhoa (kg/m)', 'swgdn (W/m)','cldtot' are being used to train the model. The correlation analysis indicates that each of these features has a significant relationship with the target variables, which suggest that these variables have an influence on the COP. By performing feature selection, it will not only improve the model's performance but will also help reduce overfitting by removing unnecessary columns.

5.6 Model Development

Different kinds of models are being used to predict the COP, which includes the machine learning models such as Random Forest, Gradient Boosting, Decision Trees, K-Nearest

Neighbor, and Support Vector Regression, Voting Regressor, and the deep learning models like Long Short-Term Memory (LSTM) (Eom, Y.H. *et al.* (2021)) and Multi-Layer Perceptron (MLP) (Küçüktopcu, E. 2023) are also used.

The study uses several machine learning models to predict the Coefficient of Performance of heat pumps. As some of these models are single output model like Gradient Boosting Regressor, Support Vector Regressor and Voting Regressor, these models are wrapped using Multioutput Regressor which helps these models to predict multiple target variables by training the model separately for every target variable and then combine them to get the final prediction. The Voting Regressor is also employed which is an ensemble method and is implemented using the Voting Regressor from the scikit-learn library, this method combines the predictions from Gradient Boosting and Support Vector Regressor. These models are used as their performance was better compared to other models. The main aim of using Voting regressor was to combine the strengths of these two models and experiment whether the outcome could be better than these two models.

Keras library is used to develop the LSTM model (Eom, Y.H. *et al.* 2021). LSTM is used for time series data because the model can maintain and learn from long-term patterns using their cell structures, which helps make better predictions. The input data was changed to a three-dimensional array to fit the data to the LSTM architecture. The LSTM model consists of four layers the input and output layer, two LSTM layers and a dense layer, with different units like 100, 50 & 32. The model is being trained for 50 epochs with a batch size of 32,to maintain a balance between the computation speed and the performance of the model. The model uses 'adam' optimizer, to adjust the learning rates and uses Mean squared error as the loss function, that allows the model to reduce the error between the predicted and actual values. MLP (Küçüktopcu, E. 2023) is also being developed using Keras library, it is a type of artificial neural network model. MLP model consists of five layers, which includes the input and output layer and three hidden layers, the hidden layers are used to capture patterns form the data by using different parameters, in this case hidden layers contains different set of units from 256 to 32 units and an activation function called ReLU. The model is being trained using backward propagation and similar to the LSTM model 'adam' optimizer and , 'mean_squared_error' loss function is used.

The following table shows the types of hyperparameters used for each model.

Model	Hyperparameter	Value
Random Forest	n_estimator	100
	max_depth	10
	min_samples_split	5
	min_samples_leaf	2
	random_state	42
	n_jobs	-1(Parallel Processing)
Decision Tree Regressor	max_depth	8
	min_samples_split	10
	min_samples_leaf	5
	random_state	24
K-Nearest Neighbour	n_neighbours	7
	weights	Distance
	algorithm	Auto
	leaf_size	30
	p	2 (Minkowski Distance)

Support Vector Regressor	kernel c epsilon gamma	RBF 1.0 0.1 Scale
LSTM Model	units return_sequences dense_layer output_layer optimizer loss epochs batch_size	100, 50 True, False 32 units, ReLU activation Units=y_train.shape[1] Adam Mean Squared Error 50 32
MLP Model	dense_layer output_layer optimizer loss epochs batch_size	256, 128, 64, 32 units & ReLU activation Units=y_train.shape[1] Adam Mean Squared Error 50 32

Table 2 Hyperparameter Settings

6 Evaluation

The performance of all the models is being evaluated using regression evaluation metrics and, learning curves to identify the training and validation error. The regression metrics includes Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). These metrics gives an understanding of the model capabilities to predict the target variables.

The Mean Absolute Error is used to measure the average magnitude of the errors between the predicted and the actual values, which provides an insight about prediction accuracy. A lower MAE indicates better model performance.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

The Mean Squared Error, evaluates the model by calculating the average squared differences between the predicted and actual values, which is used to identify large errors. A lower MSE means the model has fewer large errors.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

The R-squared is used to calculate the variance in the target variable that can be predicted using the independent variables. If the R^2 value is close to 1 it means that the model is good and fits the data well, and the accuracy of the model is high.

$$R^2 = 1 - \frac{RSS}{TSS}$$

In addition to these evaluation metrics, learning curves is also used to evaluate the performance of each machine learning model. Learning curves gives insights about how the performance of the model changes as the size of training data increases. The learning curve plot provides the training error and validation error in the form of two lines one line represents the training error, which measures the model's performance on the training data and the second line represents validation error, which measures how well the model performs on unseen data. These two lines provide insights whether the model is overfitting or underfitting by analyzing the gap in between the two lines. When the gap between the training and validation error decreases as the training size increase, that means the model is good and its learning as the size of data increases.

$$Y = aX^b$$

6.1 Experiment 1 – Machine Learning Approach

Different types of Machine Learning model are used being to predict the Coefficient of Performance (COP) of different types of heat pumps, in this experiment. The models which are used in this experiment include Random Forest, Gradient Boosting, Decision Trees, K-Nearest Neighbors (KNN), and Support Vector Regression (SVR). These models are used because each model has their strengths and weakness in terms of handling the data. As discussed in the evaluation section the same metrics are used to evaluate each model. The aim of this experiment is to identify the machine learning model which best fits the data and is able to predict the COP accurately, analyze the model's strengths and weaknesses and also understand the impact of different model on the COP prediction.

Model	MAE	MSE	R - Square	Computation Time(s)
Random Forest	0.049	0.006	0.86	26.26
Gradient Boosting Regressor	0.055	0.007	0.96	125.08
Decision Tree Regressor	0.069	0.013	0.94	1.09
KNN Regressor	0.083	0.017	0.92	1.68
SVR	0.069	0.010	0.95	243.13
Voting Regressor	0.059	0.008	0.96	191.86

Table 3 Machine Learning Model Results

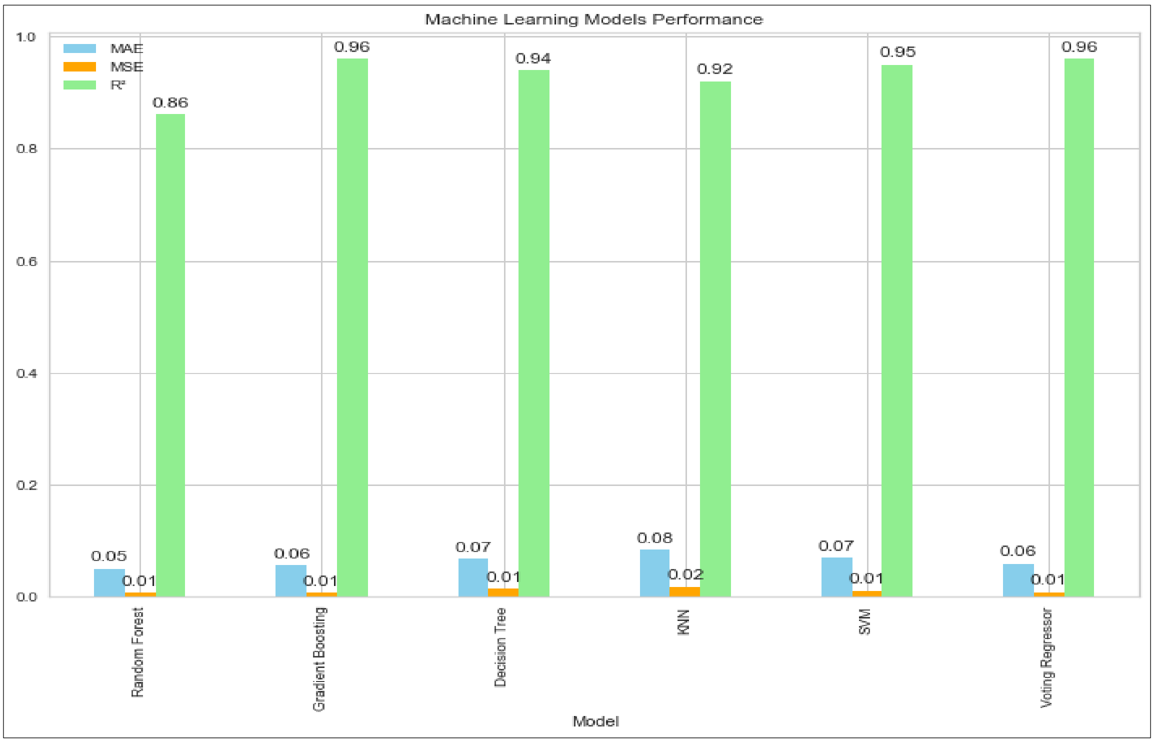

Figure 9 Comparison Machine learning model's

From table 3 and Figure 9 it can be clearly seen that the techniques like Gradient Boosting Support Vector Regression and Voting Regressor has performed better than other models, as Gradient Boosting and Voting Regressor performed slightly better than SVR which indicates that combining multiple models to form an ensemble can significantly enhance predictive performance by capturing a broader range of patterns and reducing the risk of overfitting to the training data. This superior performance suggests that ensemble methods are particularly effective in handling complex regression tasks with multiple target variables, leading to more robust and accurate predictions

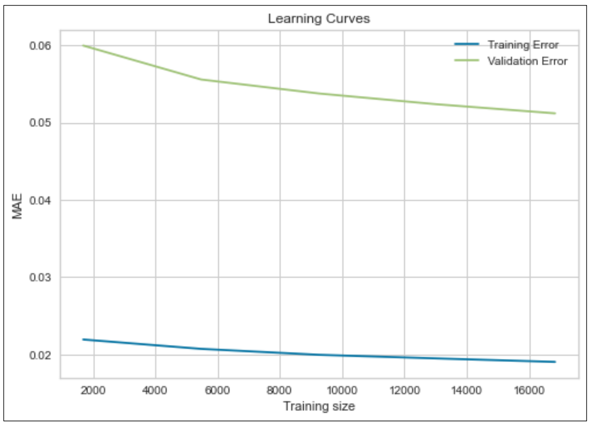

Figure 10 Training and Validation error of Random Forest

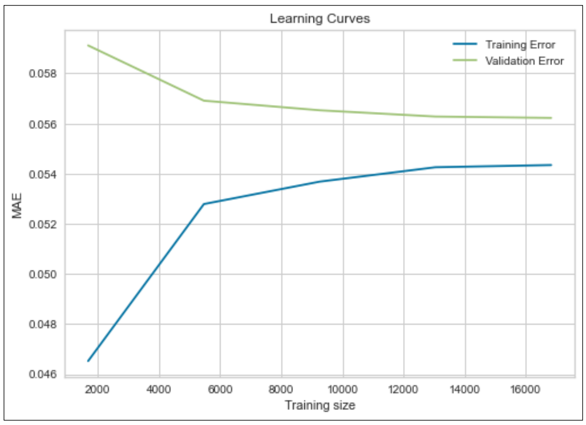

Figure 11 Training and Validation error of Gradient Boost

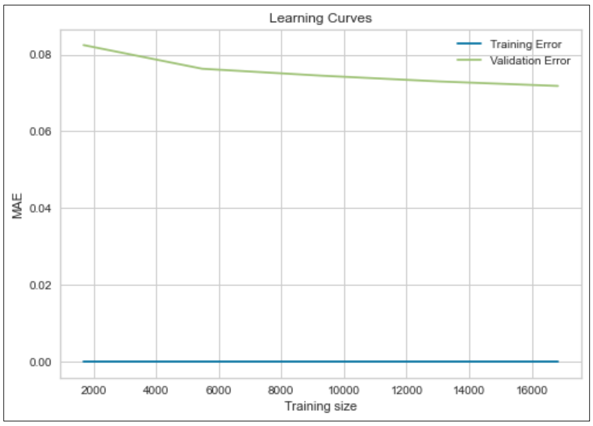

Figure 12 Training and Validation error of Decision Tree

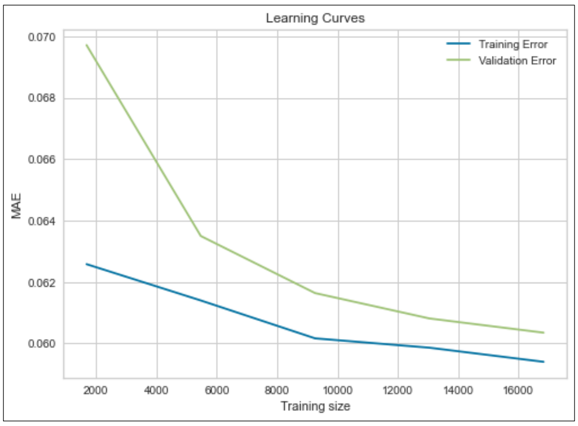

Figure 13 Training and Validation error of Voting Regressor

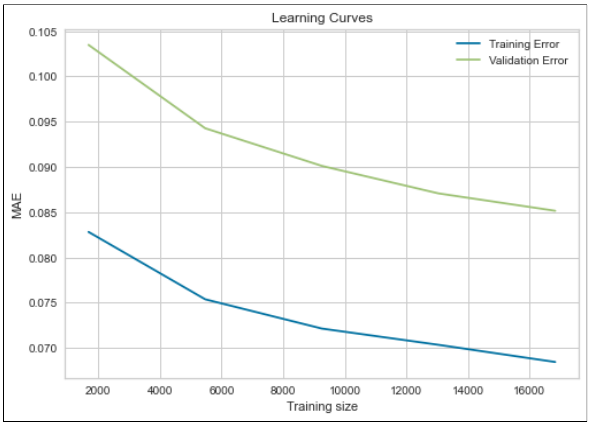

Figure 14 Training and Validation error of KNN

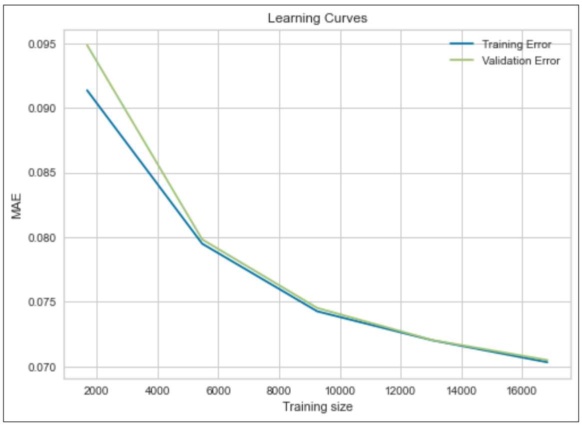

Figure 15 Training and Validation error of SVR

The above figures show the training and validation error of the machine learning models, the figures 10, 12 and 14 clearly shows that model's random forest, decision tree & KNN have larger gap between the two lines this indicates that these model and not able to generalize well to the new data. The large gap indicates that these models perform well on the training but fail to perform in the same way on the unseen data. But the figures like 11, 13 and 15 indicates that these models are performing good on the new data, because as the training size is in increasing the gap is reducing. In figure 11 Gradient Boosting model, the training error is increased with the training size, this is because as the training size increases the model has to generalize more, this can lead to higher error on the training set. The validation error is decreased as the training size increases this indicates that model is able generalize well on the new data. Also, the gap between the lines is small, this indicates that the model is not overfitting. Similarly in figure 13 voting regressor, both the training and validation error is decreased with the increase in the training size and also the gap is narrowed with both the curves showing a downward trend, this indicates that the model is becoming more generalized and continues to improve with the increasing data.

Figure 15 about SVR, here it is clear that SVR indicates the ideal scenario, even though the R-square score turned about to slightly less than the Gradient Boost and Voting Regressor models, SVR is able to perfectly fit with the new data. Here, both the training and validation error has been reduced as the training size has increased, the gap is minimal between the two lines to a point of stability and the curve showed a downward trend. It can be concluded that Gradient Boost, Voting Regressor and SVR turned out to be the best performing model among all the other models. They were able to generalize well with new data, while reducing both the training and validation error as the volume of data increased.

6.2 Experiment 2 – Deep Learning Approach

In this experiment, two deep learning models are used to predict the target variables. Long Short-Term Memory (LSTM) networks and Multi-Layer Perceptron's (MLP) models are being used in this experiment, both the models are known to handle complex and non-linear relationships in time series data. The evaluation metrics for these models are, similar, to those for the machine learning models. This experiment aims to find the most effective deep learning technique in predicting the COP and then compare it to the performance against machine learning models.

Model	MAE	MSE	R-Square	Computation Time (s)
LSTM	0.064	0.009	0.84	315.32
MLP	0.061	0.008	0.85	162.25

Table 4 Deep Learning model Results

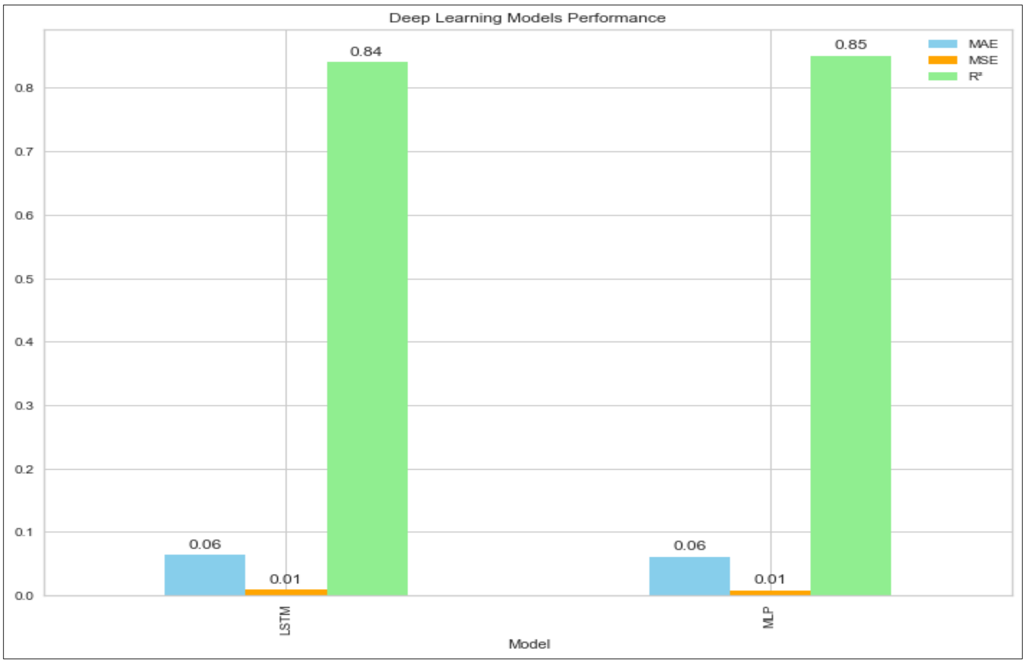

Figure 16 Comparison Deep learning model's

6.3 Discussion

The evaluation of the machine learning models and deep learning models provides some valuable insights in predicting the Coefficient of Performance of heat pump.

In the case of machine learning models, Gradient Boosting Regressor, Support Vector Regression (SVR) and Voting Regressor performed better than other model, as the models achieved a high R-squared value of 0.96, 0.95 and 0.96, respectively which indicates that the models can capture the non-linear patterns. The Gradient Boosting Regressor, showed a slightly less MAE of 0.055 than Voting Regressor MAE of 0.059, which suggest a little bit better accuracy of Gradient Boost. SVR model was able the fit the extremely well as seen in the above section compared to all the other models. The Random Forest Regressor also performed well, with an R^2 of 0.86 and low MAE of 0.049, which highlights the ability to handle complex data. Also, Decision Tree Regressor, showed good accuracy of 94%. The KNN Regressor, achieved a R^2 of 0.92, but also resulted in higher MAE of 0.083, which indicates less accuracy in the predictions. The Voting Regressor, which is an ensemble method combined with Gradient Boosting and SVR, provided a balanced approach by combining the strengths of both the models. It achieved a much better accuracy of 96%, which indicates that ensemble techniques can significantly improve the performance by reducing model variance and improving stability.

Experiment 2 focused on the performance of deep learning models, like Long Short-Term Memory (LSTM) and Multi-Layer Perceptron's (MLP). The LSTM model, with an MAE of 0.064 and MSE of 0.009, demonstrates it can learn pattern over time and can handle complex changes in the data related to COP predictions. However, the LSTM model achieved an R-squared value of 0.84 which, is less than some of the traditional machine learning models. The MLP model, which scored less MAE of 0.61 and MSE of 0.008 in comparison with LSTM models, this indicated that the model was able to understand the complex relationships within the dataset. The R-squared value of 0.85 shows that MLP can handle some complex pattern.

The comparative analysis of machine learning and deep learning models indicated that the all the machine learning models showed better performance than the deep learning models, in particular the methods like Support Vector Regression, Voting Regressor and Gradient Boosting, performed much better that any of the deep learning models in terms of predictive accuracy for this specific task. This outcome might be because the dataset, was not that complex enough to have required the advanced learning power of deep learning models. Lastly, while traditional machine learning models showed superior performance in this study, deep learning models, particularly LSTM, may benefit from further optimization. It can be concluded that the models SVR (95% accuracy), voting regressor (96% accuracy) and Gradient boosting regressor (96% accuracy), are the best models in predicting the Coefficient of Performance of heat pumps.

7 Conclusion and Future Work

The main aim of this research study is to include the heat sinks and heat sources data to predict the coefficient of performance of different types of heat pumps like ASHP , GSHP and WSHP with different heat sinks like radiator, floor heating and water heating. This research has also used weather data to understand the factors that affects the COP by combining the weather data and the heat pump data. While exploring the data it was found that ambient temperature is the most influential factor and positively correlated with the performance and air density has a negative correlation on the performance of heat pump. The study compared different machine learning models, such as Gradient Boosting Regressor, Voting Regressor, and Random Forest Regressor, Support Vector Regression, Decision Tree and KNN with deep learning models like Long Short-Term Memory (LSTM) and Multi-Layer Perceptron's (MLP). After evaluating these models using the evaluation metrics it was found that the machine learning models, especially the ensemble methods, is better in terms of the prediction accuracy for this specific task. The Gradient Boosting Regressor and Voting Regressor emerged as the best models, with an accuracy of 96%, which indicates their ability to capture non-linear patterns. Overall, it can be concluded that some machine learning models, turned out to be highly effective in predicting the COP of heat pumps like Support Vector Regression with an accuracy of 95%, Gradient Boosting with an accuracy of 96% and Voting Regressor with an accuracy of 96%.

Future research in this field can be focused on the using more complex and diverse datasets which includes some additional features and data points about the different components of a heat pump which could be used to access the full potential of the deep learning models and achieve even more better result. In addition, more deep learning models can be used and the models like LSTM and MLP can be explored by using different architecture, hyperparameters and training techniques to achieve better results. By addressing these areas, it would be possible to the develop more accurate, efficient, and reliable predictive models for heat pump performance.

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