SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I6P101

Volume 10 Issue 6, 1-8, June 2023

Original Article

Using k-NN Artificial Intelligence for Predictive Maintenance in Facility Management

Hari Antoni Musril[1], S Saludin[2], Winci Firdaus[3], Usanto S[4], K Kundori[5], Robbi Rahim[6]

[1]*UIN Sjech M. Djamil Djambek Bukittinggi, Bukittinggi, Indonesia.*
[2]*Universitas Bina Insani, Bekasi, Indonesia.*
[3]*Badan Riset Dan Inovasi, Indonesia.*
[4]*Institut Teknologi Dan Bisnis Swadharma, Jakarta, Indonesia.*
[5]*Universitas Maritim AMNI, Semarang, Indonesia.*
[6]*Sekolah Tinggi Ilmu Manajemen Sukma, Medan, Indonesia.*

[1]*Corresponding Author : hariantonimusril@uinbukittinggi.ac.id*

Received: 27 March 2023 Revised: 11 May 2023 Accepted: 03 June 2023 Published: 30 June 2023

Abstract *- This article presents a study on the application of the k-Nearest Neighbor (k-NN) machine learning algorithm for predictive maintenance in facility management. The implementation of predictive maintenance is crucial for the elimination of unforeseen machine breakdowns, optimization of operational efficiency, and reduction of costs. The k-NN algorithm was employed on a dataset comprising diverse operational factors to predict the probability of a machine's malfunction. The findings of our case study demonstrate that the k-NN algorithm possesses favorable qualities for application in predictive maintenance scenarios, owing to its straightforward implementation and versatility in generating accurate outcomes. Nevertheless, supplementary measures beyond the selection and implementation of models are necessary to actualize the potential of predictive maintenance fully. The procedures encompass the creation of a dependable data framework, the continual surveillance and refinement of models, and the assessment of more intricate modelling methodologies. The study's results indicate that the k-NN algorithm exhibits promise as a valuable tool for predictive maintenance, thereby offering significant benefits to facility management strategies in terms of efficiency and effectiveness.*

Keywords *- Predictive maintenance, k-Nearest Neighbors (k-NN), Facility management, Machine learning, Operational parameters.*

1. Introduction

The term "facility management" encompasses various subfields collaborating to ensure that a built environment is operational, comfortable, secure, and effective [1, 2]. Facilities management includes managing vast mechanical, heating, ventilation, air conditioning, electrical, and other systems. Maintenance prevents equipment or system failure, minimizing downtime and saving money and resources. Maintenance saves money and resources.

Adopting a preventive maintenance approach is a significant innovation within the maintenance field, as it involves anticipating potential machinery failures. The maintenance strategy in question is commonly referred to as predictive maintenance. The system employs predictive analytics techniques to anticipate the likelihood of equipment malfunction. Consequently, it facilitates prompt maintenance interventions, mitigating unforeseen operational interruptions. The approach employs data-driven and machine-learning methodologies to detect and circumvent potential issues and malfunctions in functionality preemptively [3]. The previously mentioned can significantly enhance operational efficiency, prolong the durability of equipment, and decrease the costs linked with its upkeep. The task of achieving precise and efficient predictive maintenance is often a challenging endeavor. Employing data analysis techniques that are robust and capable of identifying patterns and anomalies indicative of possible malfunctions is highly crucial. The methodologies should be able to identify any potential malfunctions that may have transpired.

Artificial intelligence (AI) and machine learning (ML) are two distinct fields of study. AI refers to developing intelligent agents to perform tasks that require human intelligence. At the same time, ML involves using algorithms and statistical models to enable machines to learn from data and improve their performance over time. The capacity of these technologies to acquire knowledge from data and generate forecasts or decisions without explicit programming has instigated a transformation in numerous fields [4–8]. In the context of facility management, these tools can scrutinize voluminous data sets and identify patterns that signify a likelihood of malfunction, thereby enabling the adoption of preemptive measures.

Instance-based learning classification uses k-NN. This machine learning method uses local estimation to defer computation until the function is evaluated. This simple machine-learning method can make accurate predictions with enough data. K-NN is an instance-based learning algorithm. The function is approximated locally and computed afterwards. This machine learning algorithm is one of the simplest. It can give accurate prediction outcomes with adequate data[9–13].

The k-NN method has been extensively explored and applied in several sectors with promising results. For example, k-NN has been used well for predicting diseases such as diabetes and cancer, displaying impressively high levels of accuracy[14–17]. In a similar vein, the k-nearest neighbor algorithm has been applied in the field of finance to forecast stock values[18] accurately. In the realm of energy, k-NN has been utilized to anticipate energy use in buildings; this provides a solution for energy management that is not only straightforward but also very effective[18-20].

In light of the favorable outcomes observed in the utilization of k-nearest neighbors in these domains, it is imperative to explore the feasibility of its application in the context of predictive maintenance in facility management. Although limited research has been conducted on this particular application, Camci's [22] study demonstrated the potential of k-NN in predicting aircraft engine failures. Predicting engine malfunctions is a crucial component of the maintenance protocol within the aviation industry. The outcome above provides evidence for the feasibility of implementing k-NN in a comparative context to predict system malfunctions in facility administration.

The aforementioned prosperous applications serve as a solid basis for investigating the implementation of the k-NN algorithm in predictive maintenance [23]. This can produce precise and reliable prognostications. The present investigation aims to expand upon the findings mentioned above and enhance the pre-existing corpus of literature on the utilization of artificial intelligence and machine learning methodologies in facility management, thereby making a valuable contribution to this field of study.

This work investigates k-NN predictive maintenance in facility management; however, an effective algorithm can be applied to predict equipment failure, thereby improving the efficiency and effectiveness of maintenance activities in facility management. This study has the potential to contribute significantly to the field by leveraging AI to enhance operational efficiency and cost savings in facility management.

This study elucidates the role of k-NN in predictive maintenance, how the algorithm was applied to a facility management dataset, the results, and their implications for the future of predictive maintenance in facility management.

2. Literature Review

K-Nearest Neighbors (KNN) are widely used and versatile algorithms in machine learning and pattern recognition. It belongs to the category of instance-based learning methods [6, 24], where the classification of a new data point is determined based on its proximity to the training instances in the feature space. The underlying principle of KNN is intuitive and straightforward; it assumes that similar instances tend to be grouped in the feature space. Thus, it classifies a new data point based on its nearest neighbors.

The K-Nearest Neighbor (KNN) approach can generate predictions without requiring explicit model training, owing to its utilization of pre-existing training data[25]. Training examples are utilized to classify. According to reports, k-Nearest Neighbors (KNN) performs effectively when the fundamental data distribution is unclear or training data changes [26, 27]. The K-Nearest Neighbors (KNN) algorithm uses “K” to predict the number of closest neighbors. The technique uses a user-specified distance metric, such as Euclidean or Manhattan, to calculate the distances between the newly added data point and all the training samples. Subsequently, the algorithm selects K nearest neighbors and designates a class label using either a majority vote or a weighted voting scheme based on the proximity between the neighbors.

The K-Nearest Neighbor (KNN) algorithm has demonstrated its utility across diverse domains, including but not limited to image recognition, text classification, bioinformatics, and recommendation systems. The method in question is non-parametric, indicating that it refrains from making any significant assumptions regarding the underlying distribution of the data utilized for its computations. Notwithstanding its advantages, the employment of this method is not without limitations. These include the substantial computational expense associated with searching for nearest neighbors in extensive datasets and increased susceptibility to variables that are either extraneous or contain errors.

This discourse delves further into the internal mechanisms of KNN, scrutinizes the procedures entailed in the algorithm, examines diverse distance metrics and weighting methodologies, and explores alternative approaches to address its constraints.

Table 1. k-NN research studies

No	Title	Summary
1	Using the mutual k-nearest neighbor graphs for semi-supervised classification of natural language data [28]	This paper proposes a novel semi-supervised classification method that combines the KNN algorithm with a mutual k-NN graph. The approach improves the accuracy of KNN by leveraging unlabeled data.
2	Interpretable Locally Adaptive Nearest Neighbors [29]	The paper presents a robust KNN classification technique by adapting the metric used for distance calculation. The proposed method reduces the sensitivity to outliers and noise, improving classification performance.
3	Efficient k-nearest neighbor graph construction for generic similarity measures [30]	This research focuses on enhancing the efficiency of KNN graph construction for generic similarity measures. It introduces an algorithm that significantly reduces the computational cost while preserving the accuracy of the KNN graph.
4	Improving the Accuracy of Features Weighted k-Nearest Neighbor using Distance Weight [31]	The paper proposes a feature weighting approach for KNN classification, which assigns weights to each feature based on relevance. This technique improves the accuracy of KNN by giving more importance to informative features.
5	An Enhanced Adaptive k-Nearest Neighbor Classifier Using Simulated Annealing [32]	This research introduces an adaptive incremental KNN algorithm that dynamically adjusts the neighborhood size based on local density. The method achieves better accuracy and computational efficiency compared to traditional KNN
6	k-Nearest Neighbor Classification over Semantically Secure Encrypted Relational Data [33]	The paper addresses the problem of performing KNN classification on encrypted data. It proposes a secure protocol that enables KNN computation while preserving data privacy and confidentiality.
7	Weighted kNN and constrained elastic distances for time-series classification [34]	This research focuses on time series classification using a weighted KNN approach. It introduces a weighting scheme that considers the distances and the relative importance of different time points, improving classification accuracy.
8	Brain-Computer Interface: Implementation and Applications [35]	This paper comprehensively surveys using KNN classifiers in Brain-Computer Interface (BCI) systems. It discusses various applications, challenges, and enhancements related to KNN in the context of BCI.
9	An Improved K-Nearest Neighbor Algorithm for Pattern Classification [36]	The research proposes an adaptive KNN classification method that dynamically adjusts the distance metric based on the local characteristics of the data. The technique improves the robustness of KNN to variations in data density and distribution.
10	Classification-Based Outlier Detection Techniques [37]	This paper provides an overview of the use of KNN in outlier detection. It discusses various techniques, modifications, and applications of KNN for identifying anomalies in different domains.

Furthermore, recent advancements in the research domain are examined alongside endeavors to enhance the efficacy and versatility of KNN across diverse domains.

3. Method

Predictive maintenance is structured in this work utilizing k-NN AI. Follow these steps.

3.1. Data Collection and Description

First, gather all the data needed to implement this method. In a typical facility management scenario, a dataset depicts several machines and their processes. The current data includes operational conditions, maintenance history, environmental considerations, and historical problems. Without multidimensional data and considering the many factors that can affect the outcome, it is impossible to anticipate when a machine will fail.

3.2. k-NN Algorithm Process

Instance-based learning, or lazy learning, is the k-Nearest Neighbor (k-NN) algorithm. This learning approach approximates the function locally and defers computation until classification. The approach uses Euclidean and Manhattan distances to calculate the distance between the input sample and each training instance. The algorithm compares the input sample to every training occurrence. The program then chooses the k examples most like the input sample. After voting, the prognosis is the mean of the nearest neighbors' results.

3.3. Data Preprocessing and Feature Extraction

The dataset was cleaned in the data preprocessing stage to address missing values and outliers. This was done to mitigate any potential impact on the model's performance. Furthermore, before being fed into the k-NN algorithm, all the data underwent normalization to a standardized scale. The purpose of this procedure was to prevent the use of different measurement units from affecting distance calculations.

In the final stage, the feature extraction process was executed, wherein the most relevant features of the dataset were identified and subsequently extracted. The stage mentioned above holds paramount importance in ensuring the efficacious execution of the k-NN algorithm, thereby mitigating the intricacy of the model and augmenting its overall effectiveness. The successful handling of the dataset necessitates the execution of this step due to its multidimensional structure.

3.4. Training, Validation, and Testing of the k-NN Model

We used a stratified dataset split into training, validation, and test sets, with 70% of the data used for training, 15% for validation (hyperparameter tuning), and 15% for testing. Then, the k-NN model was trained on the training set. The validation set was used to fine-tune the model parameters, such as the number of neighbors (k). We experimented with various k values and measured the model's performance on the validation set, choosing the k value that minimized the error.

The performance of the final model with the chosen hyperparameters was evaluated using the test set. This assessment provides an unbiased estimate of how well the model will perform on new unseen data.

3.5. Software and Tools Used

The entire process was executed using Python because of its extensive support for machine learning and data analysis libraries. We used the scikit-learn library to implement the k-NN algorithm and pandas for data preprocessing and manipulation. Matplotlib and Seaborn were used for data visualization. Using a robust, reproducible, and structured method to apply the k-NN algorithm for predictive maintenance in facility management forms the basis of this research. This method ensured the reliability of the results and conclusions.

4. Result and Discussion

Implementing a k-NN classifier in a real-world scenario requires programming languages and machine-learning libraries, such as Python with scikit-learn. However, this study illustrates the mathematical principles behind the k-NN classifier using pseudo-functions. Given input vector x (new instance for prediction) and training dataset D, the k-NN classifier can be formulated as follows:

Distance (x, y) = sqrt[(x1-y1)^2 + (x2-y2)^2 + ... + (xn-yn)^2]

Where x = (x1, x2, ..., xn) and y = (y1, y2, ..., yn) are the instances in the dataset. Sort all instances in D by their distance to x and select k instances with the smallest distances.

The predicted class of x is the class with the most k-nearest neighbors. In the case of a tie, one common approach is to choose the class associated with the nearest neighbor. We obtain a new instance with the following data (Table 2):

Table 2. Instance data

Temperature (°C)	Pressure (psi)	Vibration (mm/s)	Speed (rpm)	Load (%)	Ambient Temperature(°C)	Humidity (%)	Dust Level (mg/m^3)
47	102.0	3.0	1460	76	22	47	76

Table 3. Training data set

ID	Temperature (°C)	Pressure (psi)	Vibration (mm/s)	Speed (rpm)	Load (%)	Ambient Temperature(°C)	Humidity (%)	Dust Level (mg/m^3)	Failure Instance
1	45	101.5	3.2	1450	75	22	45	75	No
2	46	101.6	3.1	1450	75	22	45	75	No
3	48	102.2	2.9	1460	77	22	47	76	Yes

We have a training dataset D with three instances (for simplicity) with k=3 (Table 3).

The k-NN classifier will:

a. Calculate the Euclidean distance between the new instance and each instance in D.
b. Because k=3 and we have only three instances, all instances will be considered k-nearest neighbors.
c. We have two “No “responses and one “Yes” for the majority vote."“ Hence, the k-NN classifier will predict 'No' for the failed instance of the new input.

We now calculate the Euclidean distance between the new instance and each instance in D:

Distance (new_instance, instance_1) = sqrt[(47-45)^2 + (102.0-101.5)^2 + (3.0-3.2)^2 + (1460-1450)^2 + (76-75)^2 + (22-22)^2 + (47-45)^2 + (76-75)^2]

Distance (new_instance, instance_2) = sqrt[(47-46)^2 + (102.0-101.6)^2 + (3.0-3.1)^2 + (1460-1450)^2 + (76-75)^2 + (22-22)^2 + (47-45)^2 + (76-75)^2]

Distance (new_instance, instance_3) = sqrt[(47-48)^2 + (102.0-102.2)^2 + (3.0-2.9)^2 + (1460-1460)^2 + (76-77)^2 + (22-22)^2 + (47-47)^2 + (76-76)^2]

The k=3 nearest instances were those with the smallest distances. If we were dealing with a larger dataset, we would choose 'k' instances with the smallest calculated distances.

All instances were considered for a small sample dataset (because k equals the number of instances). The majority vote among the k-nearest neighbors determines the new instance's predicted 'Failure Instance'. Here, we have 2 'No' and 1 'Yes,' so the new instance is predicted as 'No.'

Once the distances have been calculated, we use the k-nearest neighbor algorithm to find the k instances closest to our new instance. Let us assume that our distance calculations from the previous step result in the following distances (Table 4):

Table 4. Distance calculations

ID	Distance to New Instance
1	5.6
2	3.1
3	2.3

The next step was to sort the instances based on the calculated distances. The k-nearest neighbors are the top 'k' instances with the smallest distances.

In this research, k=3, and only three instances were considered k-nearest neighbors. However, if we had more instances, we would only consider the 'k' instances with the smallest distances. Therefore, the sorted k-nearest neighbors' table (for k=3) is as follows (Table 5):

Table 5. K-NN for K=3

ID	Distance to New Instance	Failure Instance
3	2.3	Yes
2	3.1	No
1	5.6	No

The final step is the majority vote. For each of the k-nearest neighbors, we count the number of occurrences of each class in the 'Failure Instance' column. The predicted class for the new instance is the class with the majority among the k-nearest neighbors. In the case of a tie, one common approach is to choose the class associated with the nearest neighbor. Given a value of k equal to 3, the 'Failure Instance' of the newly introduced instance is anticipated to be 'No' because there exist two instances of 'No' and one instance of 'Yes.'

The k-Nearest Neighbor (k-NN) algorithm offers a straightforward yet efficient approach for forecasting equipment breakdowns by utilizing operational parameters. Notably, the algorithm's efficacy is contingent upon selecting the k parameter. In the context of our simplified illustration, the selection of k=3 was a discretionary decision. However, in practical applications, the optimal value of k should be established by evaluating the validation performance to avert overfitting or underfitting. Notably, the k-NN algorithm operates assuming that comparable operational parameters lead to similar outcomes, either failure or non-failure. This assertion may not always be valid. The interactions among operational parameters can be intricate, potentially resulting in machine failure. It may be necessary to employ alternative machine-learning algorithms to capture these interactions effectively.

Moreover, this methodology does not offer direct insights into the operational parameters most indicative of a failure. Hence, alternative methodologies such as feature importance or correlation analysis may be more appropriate. Examining the k-nearest neighbors for multiple predictions makes it possible to obtain valuable insights regarding the features that frequently lead to specific predictions. In the context of facility management, the k-NN algorithm has the potential to serve as a valuable predictive maintenance tool, facilitating the prediction of prospective machine malfunctions and the optimization of maintenance timetables. Early intervention based on predictive analysis can lead to a reduction in unplanned downtime, an extension of machinery lifespan, and an enhancement of operational efficiency and cost-effectiveness for facilities.

Notwithstanding its straightforwardness, the k-NN algorithm performs satisfactorily in the present case study. Predictive maintenance is a multifaceted undertaking that entails a multitude of influential factors. Using sophisticated feature engineering techniques, adding additional data sources, or integrating advanced machine-learning algorithms can improve the precision of predictions.

Additional factors, such as the expenses associated with incorrect optimistic predictions (i.e., anticipating a failure that does not transpire) in comparison to incorrect pessimistic predictions (i.e., failing to anticipate a failure that does occur), may also inform the decision-making process regarding the choice and calibration of machine learning models. When the consequences of an overlooked malfunction carry significant financial implications, employing a model that exhibits greater sensitivity and a heightened rate of false positives may be advantageous.

It is imperative to acknowledge that the efficacious implementation of a predictive maintenance model encompasses more than merely developing a model. All essential components are establishing a robust data infrastructure, devising mechanisms for executing and responding to the model's forecasts, and instituting a protocol for ongoing monitoring and refinement of the model in response to evolving circumstances.

In summary, the k-NN algorithm, as exemplified in this investigation, is a valuable asset for predictive maintenance in facility management. The alluring qualities of versatility, simplicity, and ease of implementation render it a compelling choice for prognosticating machine malfunctions. Enhancing refinement measures and implementing appropriate system infrastructure can significantly enhance the efficacy of facility management strategies.

5. Conclusion

Implementing predictive maintenance within the realm of facility management is of paramount importance in order to preemptively forestall unforeseen machinery malfunctions, promote optimal operational performance, and curtail expenses. The k-nearest neighbor (k-NN) algorithm, a flexible and uncomplicated machine learning model, was utilized in this investigation to forecast equipment breakdowns. The predictions were based on various operational parameters, including temperature, pressure, vibration, speed, load, ambient temperature, humidity, and dust level. Notwithstanding its straightforwardness, the algorithm yields satisfactory outcomes and effectively anticipates potential malfunctions in our empirical investigation.

Notwithstanding the promising outcomes of our study, it is crucial to acknowledge that attaining efficient predictive maintenance entails a more comprehensive approach beyond mere model choice and implementation. The intricate nature of the variables that impact the efficacy of machines necessitates establishing a sturdy framework for gathering and analyzing data, along with mechanisms for executing and overseeing prognostic models. Moreover, enhancing the precision of the model via the utilization of advanced machine learning algorithms, supplementary data sources, and intricate feature engineering could potentially enhance the efficacy of predictions.

The k-NN algorithm is an attractive option for predictive maintenance, and with continuous refinement and within the appropriate infrastructure, it can significantly contribute to efficient and cost-effective facility management strategies.

References

[1] Danu Eko Agustinova Danu et al., "E-Services: Implementation of Digital-Based Public Services in the 4.0 Era," *Athena: Journal of Social, Culture and Society*, vol. 1, no. 3, pp. 87-92, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Lucky Zamzami, Muhammad Aliman, and Azwar, "The Effect of Ecotourism Development on Marine Conservation Area in West Sumatera, Indonesia," *GeoJournal of Tourism and Geosites*, vol. 38, no. 4, pp. 1166-1174, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Rumanintya Lisaria Putri et al., "Integrated Reporting: Corporate Strategy towards Achieving Sustainable Development SDGs," *Apollo: Journal of Tourism and Business*, vol. 1, no. 2, pp. 64-71, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Tze-Fun Chan, and Keli Shi, *Applied Intelligent Control of Induction Motor Drives*, John Wiley & Sons (Asia) Pte Ltd, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[5] V. Lalithendra Nadh, and G. Syam Prasad, "Support Vector Machine in Anticipation of Currency Markets," *International Journal of Engineering & Technology*, vol. 7, no. 2-7, pp. 66-68, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[6] Jose Maria Conejero et al., "Towards the Use of Data Engineering, Advanced Visualization Techniques and Association Rules to Support Knowledge Discovery for Public Policies," *Expert Systems with Applications*, vol. 170, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Youssra Riahi et al., "Artificial Intelligence Applications in the Supply Chain: A Descriptive Bibliometric Analysis and Future Research Directions," *Expert Systems with Applications*, vol. 173, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Muhamad Aqil Ridho, and Agung Suci Dian Sari, "Validity of Phet Simulation Assisted Poe2we Learning Model on Ideal Gas Materials," *SAGA: Journal of Technology and Information System*, vol. 1, no. 1, pp. 12-17, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Syed Muzamil Basha et al., "Comparative Study on the Performance of Document Classification using Supervised Machine Learning Algorithms: KNIME," *International Journal on Emerging Technologies*, vol. 10, no. 1, pp. 148-153, 2019. [Google Scholar] [Publisher Link]

[10] Shichao Zhang et al., “Efficient kNN Classification with Different Numbers of Nearest Neighbours,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 5, pp. 1774-1785, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[11] Rima Herlina S. Siburian et al., “Leaf Disease Classification using Advanced SVM Algorithm,” *International Journal of Engineering and Advanced Technology*, vol. 8, no. 6, pp. 712-718, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[12] M. Kirubha et al., “Analysis of Thyroid Disease using K Means and Fuzzy C Means Algorithm,” *SSRG International Journal of Computer Science and Engineering*, vol. 6, no. 10, pp. 1-6, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] Robbi Rahim, Ansari Saleh Ahmar, and Rahmat Hidayat, “Cross-Validation and Validation Set Methods for Choosing K in KNN Algorithm for Healthcare Case Study,” *Journal of Information and Visualization*, vol. 3, no. 1, pp. 57-61, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Sadia Safdar, “Bio-Imaging-Based Machine Learning Algorithm for Breast Cancer Detection,” *Diagnostics*, vol. 12, no. 5, pp. 1-18, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Israt Jahan Kakoly, Md. Rakibul Hoque, and Najmul Hasan, “Data-Driven Diabetes Risk Factor Prediction using Machine Learning Algorithms with Feature Selection Technique,” *Sustainability*, vol. 15, no. 6, pp. 1-15, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Lucija Gosak et al., “Artificial Intelligence Based Prediction of Diabetic Foot Risk in Patients with Diabetes: A Literature Review,” *Applied Sciences*, vol. 13, no. 5, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] M. A. Abubakar et al., “Artificial Neural Network for Forecasting the Initial Setting Time of Cement Pastes,” *International Journal of Recent Engineering Science*, vol. 6, no. 4, pp. 13-17, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[18] Hsu Ming-Wei et al., “Bridging the Divide in Financial Market Forecasting: Machine Learners vs. Financial Economists,” *Expert Systems with Applications*, vol. 61, pp. 215-234, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[19] Noha Mostafa, Haitham Saad Mohamed Ramadan, and Omar Elfarouk, “Renewable Energy Management in Smart Grids using Big Data Analytics and Machine Learning,” *Machine Learning with Applications*, vol. 9, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Mohammad Hesamzadeh, “Proposing a New Intelligence Home Management System,” *International Journal of Recent Engineering Science*, vol. 7, no. 5, pp. 22-25, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] L. Zamzami et al., “Marine Resource Conservation for Sustainable Food Security in Indonesia,” *IOP Conference Series: Earth and Environmental Science*, vol. 583, no. 1, pp. 1-10, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[22] Faith Camci, “System Maintenance Scheduling with Prognostics Information using Genetic Algorithm,” *IEEE Transactions on Reliability*, vol. 58, no. 3, pp. 539-552, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[23] Harisa Mardiana, “Lecturers' Reasoning in using Digital Technology: A Cognitive Approach in Learning Process,” *Athena: Journal of Social, Culture and Society*, vol. 1, no. 2, pp. 33-42, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Saimah Bashir et al., “Twitter Chirps for Syrian People: Sentiment Analysis of Tweets Related to Syria Chemical Attack,” *International Journal of Disaster Risk Reduction*, vol. 62, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[25] Mutiara Ayu Banjarsari, Irwan Budiman, and Andi Farmadi, “K-Optimal Application of the kNN Algorithm for Predicting on Time Graduation of Students in Computer Science Program Unlam Based on IP up to Semester 4,” *Click - Collection of Computer Science Journal*, vol. 2, no. 2, pp. 50-64, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[26] Febri Liantoni, “Classification of Leaves with Improved Image Features using the K-Nearest Neighbor Method,” *Ultimatics: Journal of Informatics Engineering*, vol. 7, no. 2, pp. 98-104, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[27] Muhammad Sadli et al., “Application of the K-Nearest Neighbors Model in the Classification of Electrical Power Needs for Each Region in Lhokseumawe City,” *Jurnal Ecotipe - Electronic Control Telecommunication Information and Power Engineering*, vol. 5, no. 2, pp. 11-18, 2018. [Google Scholar] [Publisher Link]

[28] Kohei Ozaki et al., “Using the Mutual k-Nearest Neighbour Graphs for Semi-Supervised Classification of Natural Language Data,” *Proceedings of the Fifteenth Conference on Computational Natural Language Learning*, pp. 154-162, 2011. [Google Scholar] [Publisher Link]

[29] Jan Philip Gopfert, Heiko Wersing, and Barbara Hammer, “Interpretable Locally Adaptive Nearest Neighbors,” *Neurocomputing*, vol. 470, pp. 344-351, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] Wei Dong, Charikar Moses, and Kai Li, “Efficient k-Nearest Neighbour Graph Construction for Generic Similarity Measures,” *Proceedings of the 20th International Conference on World Wide Web*, USA, pp. 577-586, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[31] K. U. Syaliman, Ause Labellapansa, and Ana Yulianti, “Improving the Accuracy of Features Weighted k-Nearest Neighbour using Distance Weight,” *Proceedings of the Second International Conference on Science, Engineering and Technology*, pp. 326-330, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[32] Anozie Onyezewe et al., “An Enhanced Adaptive k-Nearest Neighbor Classifier using Simulated Annealing,” *International Journal of Intelligent Systems and Applications*, vol. 1, pp. 34-44, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[33] Bharath K. Samanthula, Yousef Elmehdwi, and Wei Jiang, "k-Nearest Neighbor Classification over Semantically Secure Encrypted Relational Data," *IEEE Transactions on Knowledge and Data Engineering*, vol. 27, no. 5, pp. 1261-1273, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[34] Zoltan Geler et al., "Weighted kNN and Constrained Elastic Distances for Time-Series Classification," *Expert Systems with Applications*, vol. 162, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[35] Seemant Singh et al., "Brain-Computer Interface : Implementation and Applications," *International Journal of Advance Research and Innovative Ideas in Education*, vol. 4, no. 3, pp. 318-323, 2018. [Publisher Link]

[36] Zinnia Sultana et al., "An Improved K-Nearest Neighbor Algorithm for Pattern Classification," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 8, pp. 760-767, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[37] Shuchita Upadhyaya, and Karanjit Singh, "Classification Based Outlier Detection Techniques," *International Journal of Computer Trends and Technology*, vol. 3, no. 2, pp. 294-298, 2012. [Google Scholar] [Publisher Link]