LAUTECH Journal of Engineering and Technology 18(1) 2024: 192-203

PERFORMANCE EVALUATION OF MACHINE LEARNING FOR JUDICIAL PREDICTION SYSTEM

[1]Sobowale A., [2*] Olubunmi O., [3]Esan A. and [4]Abdul-Waheed T.

[1,3]Department of Computer Engineering, Federal University Oye-Ekiti, Ekiti state, Nigeria

[2]Department of Computer Engineering, Ekiti State University, Ado-Ekiti, Nigeria

[4]Department of Electrical and Electronics Engineering, Federal Polytechnic, Ayede, Oyo State, Nigeria

(Corresponding author's email address: adewale.olubunmi@eksu.edu.ng)

ABSTRACT

A Judicial Prediction System (JPS) forecasts the judicial results based on historical data, legal precedents, and other relevant factors, thereby providing judges and other law professionals with predictive insights into case outcomes. The purpose of the JPS is to educate the public by promoting transparency in the legal process and overcoming various factors negatively influencing the final judgment such as cognitive biases, judicial bottlenecks, emotions, and so on. Artificial Intelligence and Machine Learning techniques have been productively utilized to forecast judicial outcomes and analyze them This paper aims to find the most effective way for judicial outcome prediction to assist in time and judicial resource optimization. Four distinct algorithms: Support Vector Machine, Random Forest, Logistic Regression, and K-Nearest Neighbor have been utilized to determine the appeal case outcomes at the Supreme Court of Nigeria (SCN). The dataset used in training the machine learning algorithms was obtained locally from the Supreme Court of Nigeria (SCN). The models were evaluated using accuracy, precision, recall, and F1 score. Results show that Random Forest provided the highest accuracy of 72%. However, future research should consider an ensemble approach for judicial case prediction.

Keywords: *judicial prediction system, Machine Learning algorithms, model, case outcomes, judicial precedence*

INTRODUCTION

The introduction and the use of machine learning in judicial prediction systems have proven to be a critical area of research, addressing the need for more efficient and accurate legal decision-making processes (Chen, 2018). The application of machine learning in legal domains has gained significant attention due to its potential to enhance the efficiency and reliability of judicial prediction systems. Previous studies have highlighted the successful implementation of machine learning algorithms in legal text classification (Sil & Roy, 2021), case outcome prediction (Bhilare *et al*., 2019), and risk assessment (Grogger *et al*., 2021), demonstrating the promising prospects of this technology in legal decision-making processes. With the increasing volume of legal cases and the complexity of the judicial system, there is a rapidly increasing demand for technologically advanced solutions to help in forecasting judicial case outcomes and guiding legal decision-making by analyzing past court rulings, case attributes, and judicial behavior data, these systems model the complex factors that influence rulings to provide data-driven insights and recommendations (Shi *et al*., 2021).

Previous research works have proposed and examined neural networks (Chalkidis *et al*., 2019; Strickson and De La Iglesia, 2020), support vector machines (Medvedeva *et al*., 2021), KNN (Sari,

2023), and other algorithms for tasks ranging from predicting US Supreme Court decisions (Katz *et al*., 2017) to case duration estimation (Dexter *et al*., 2022). However, the studies utilized proprietary datasets and evaluation metrics, making comparisons across different modelling approaches impossible. Furthermore, the ethical implications of deploying predictive judicial tools have not been sufficiently analyzed (Remus & Levy, 2017). Some of the popular predictive modelling algorithms that can be utilized for judgment forecasting are as follows: Support Vector Machines (SVM): SVM, a supervised machine learning algorithm suitable for classification and regression, operates by determining the optimal hyperplane for classification. This involves identifying support vectors, which are the points of each class situated at the margin, which is a fundamental principle in SVMs (Rani *et al*.,2022; Rani *et al*., 2022). Random Forest: A random forest is a set of random decision trees, resembling conventional decision trees but with randomly chosen criteria at each node. Sometimes, the selection is further relaxed by choosing the best criterion from a randomly selected subset. While an individual random decision tree may be suboptimal, a collective classifier of these trees yields improved results. Each tree, learning from a data subset, makes unique errors that do not correlate, eliminating errors when predictions are averaged across all models. Random forests (Virtucio *et al*., 2018) are efficiently trained and offer swift inference. The interpretability of individual trees makes them suitable for critical applications, such as feature selection or identifying the most relevant features in input data. Random forest has been used in court judgment analysis to predict the outcome of cases (Wang *et al*., 2019; McCandless and Haupt, 2019; Undavia *et al*.,2018). K-Nearest Neighbour (KNN): KNN (Sari, 2023) is an effective nonparametric classification method, functioning as a predictive supervised algorithm. It operates as a lazy learning method, constructing a model right before classifying a given test tuple, thereby generalizing based on the similarity of stored training tuples when a test tuple is encountered. Similarity between samples is typically measured using metrics like Euclidean distance or Marxian distance (Zhang *et al*., 2022).

This research paper presents a comprehensive comparative evaluation of four remarkable machine learning algorithms on the Supreme Court of Nigeria (SCN) judicial datasets related to appeal cases on both civil and criminal cases. The datasets and evaluation framework employed enable robust quantification and comparison of model performance with metrics including accuracy, precision, recall, and F1 score. The raw data which was collected from an online database was in the form of unstructured text-based .docx case files. These documents were processed to extract structured information into a spreadsheet format. The final structured dataset consists of 5,585 criminal and civil appeal cases brought before the Supreme Court of Nigeria (SCN) between 1962 and 2022, along with eventual SCN rulings that can be utilized for building and testing judicial prediction models (Ngige *et al*., 2023).

The contributions of this work lie in providing a comprehensive analysis of the application of machine learning algorithms in judicial prediction systems, offering insights into the potential benefits and challenges associated with their implementation. The structure of the paper will involve an in-depth review of related literature, followed by an analysis of existing judicial prediction models. Subsequently, the research methodology and the development of machine learning-based prediction models will be presented, along with the experimental results and discussions.

Finally, the paper will conclude with implications for future research and the significance of machine learning in enhancing judicial prediction systems.

Predictive Modelling is the task that entails making predictions about future events or outcomes using statistical algorithms and machine learning techniques. Predictive models are trained on historical data to identify patterns and relationships between various data points, and their main goal is to make accurate predictions about future events. Predictive modelling algorithms are a set of mathematical equations and statistical techniques used to predict an outcome or future behaviour based on historical data. These algorithms are used to build predictive models that can forecast future trends, identify patterns in data, and make data-driven decisions. They are used in a wide range of applications, including judicial prediction, to forecast likely judgment decisions that can be reached depending on the historical data supplied.

The study provides guidelines for developing fair, transparent, and ethically informed judicial prediction systems. It also sets up an extensible testbed for advancing research in explainable AI within the legal system.

Research Gap

The identified gap and challenges within the current Judicial Prediction Systems encompass issues such as black-box problems, the absence of local datasets within the local context and many of the reviewed works used unstructured data. This study has addressed these challenges by constructing models using ML techniques, which are simple and explainable for Judicial Prediction Systems using a locally acquired and structured dataset. This approach enhances the contextual relevance and tackles the problem of data specificity being faced by existing systems.

METHODOLOGY

This system aims to predict the verdict of a judicial case based on the verdict of previous SCN cases. Various prediction model was introduced in the previous section with their fair share of pros and cons and thus, this work strives to conduct the performance analysis of the mentioned algorithms. Feature extraction for the Supreme Court of Nigeria (SCN) appeal cases dataset was carried out with the use of the wrapper feature selection technique.

Dataset Acquisition and Pre-processing

Data acquisition is the very first stage in which historical data consisting of the appeal cases presented at the Supreme Court of Nigeria (SCN) were collected from an online repository (Primsol Law Pavilion). This dataset consists of civil and criminal cases with their final judgment in the corresponding column. The data was split into training and testing sets of particular size 70%-30% ratio. For the Data pre-processing, this study employed some preprocessing techniques on the dataset to put it in the right useful format. Some of the preprocessing techniques employed in this research are removing missing values, normalization, and synthetic minority oversampling technique (SMOT), among others.

Feature Selection

Feature selection is a vital step in machine learning and data mining, which involves the process of selecting a subset of relevant features (variables or predictors) from the original set of features for use in model development. The main objectives of the feature selection approach are to (i) remove irrelevant and redundant features to improve model performance,(ii) reduce the dimensionality of the data, optimising the learning process and reducing the computational complexity and (iii) identify the most important features by providing insights into the underlying problem thereby improving the

interpretability of the model (Tubishat *et al*., 2020; Kozodoi *et al*., 2019).

In this work, the wrapper feature selection technique was used to find a subset of predictors to optimise the performance of the predictive model. It can be noted from Figure 1 that the feature set search component initiates by generating a subset of features, followed by the learning algorithm assessing the quality of these features based on learning performance without knowledge of its internal operations. This iterative process continues until the optimal learning performance is attained. The feature subset yielding the highest learning performance is then identified and output as the selected features.

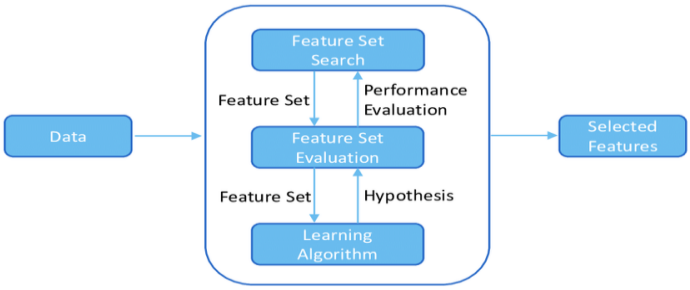

Figure 1: Wrapper Feature Selection Framework (Li *et al*., 2016)

Machine Learning Models

Machine learning provides a unique technique which are designed to identify patterns and relationships in data, and use the information obtained to build models that can make accurate predictions or decisions on new, and unseen data. Traditional Machine Learning models generally require less memory and training time in comparison to Deep Learning models, due to their simple architectures with far fewer parameters, and ability to be efficiently trained on smaller, more curated datasets, thereby reducing computation requirements. Four models namely: Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) were used for the prediction of judicial case outcomes in this study.

Support Vector Machine (SVM): SVM seeks to identify the best decision boundary (optimal hyperplane), which optimally distinguishes between instances belonging to various classes within the feature space. This optimal hyperplane is determined by maximizing the distance between the nearest points from each class, a distance referred to as the margin. By maximizing this margin, SVMs create a separation that is robust to noise and outliers, enhancing the model's ability to generalize effectively to unseen data instances. In Figure 2, the hyperplane is represented by the equation (Singh & Kaur, 2012):

$$w.x+b=0 \quad (1)$$

where w is the normal vector to the hyperplane and b is the bias or offset parameter. The margin is defined as the distance between the two parallel hyperplanes that separate the classes and are closest to the data points from each class. These hyperplanes are represented by the equations (Singh and Kaur, 2012):

$$w.x+b=1 \quad (2)$$

$$w.x+b=-1 \quad (3)$$

The objective of the SVM optimization problem is to maximize the margin, subject to the constraint

that the data points from each class lie on the correct side of the parallel hyperplanes.

The support vectors are the data points that lie closest to the optimal hyperplane and satisfy the equality

$$y_i(w^{*T}X_i + b) = 1 \quad (4)$$

These critical instances define the maximum margin and the position of the hyperplane. By maximizing the margin, the SVM model finds the decision boundary that separates the classes with the largest possible distance from the nearest data points, leading to better generalization performance and robustness to noise and outliers.

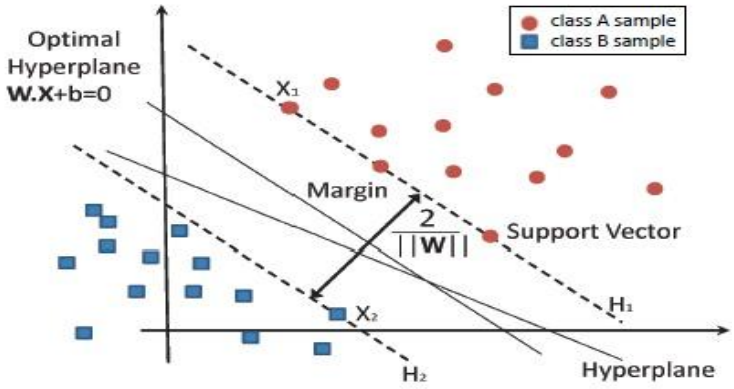

Figure 2: Data Classification using SVM (Garcia-Gonzalo *et al.*, 2016)

Nearest Neighbors (KNN): The K-Nearest Neighbors (KNN) algorithm is an instance-based, non-parametric approach to classification tasks. Instead of learning a specific model or function from the training data, KNN operates by assigning class labels to new, unseen data points based on the class memberships of their closest neighbors within the feature space (Boateng *et al.*, 2020). This classification is determined by considering the majority class among the K nearest neighboring instances, where K is a user-defined parameter. The underlying principle is that data points located in close proximity are likely to share the same class or target value.

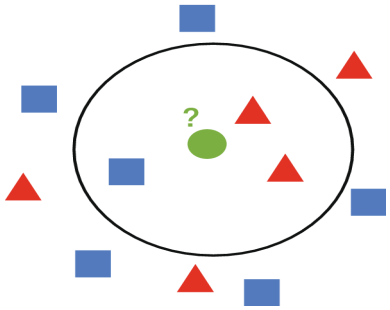

Figure 2: KNN Illustration (Li *et al.*, 2022)

The diagram in Figure 2 illustrates a 2D feature space with data points belonging to two different classes, represented by blue squares and red triangles. The new data point (green circle) is the unseen data point that needs to be classified. Based on a chosen value of K (e.g., K=5), the algorithm identifies the K nearest data points to the new point in the feature space, regardless of their class labels. The class label for the new data point is determined by the majority class among its K nearest

neighbours. If more neighbours belong to the class represented by red triangles, the new point is classified as a red triangle; otherwise, it is classified as a blue square.

Logistic Regression: Logistic Regression is a statistical modeling technique employed for binary classification problems, where the target variable takes one of two possible values or classes. Unlike linear regression, which models a continuous response variable, Logistic Regression is designed to handle categorical outcomes, which has its core principle behind estimating the probability that a given instance or data point belongs to one of the two classes (Ranganathan *et al.*, 2017). This probability estimation is achieved by applying the logistic function, also known as the sigmoid function, to a linear combination of the input features. The logistic function transforms the linear predictor into a value between 0 and 1, representing the probability of class membership. By setting a threshold on this probability, the model can assign instances to one of the two classes, enabling binary classification decisions.

Random Forest (RF): Random Forest is a commonly used machine learning algorithm that belongs to the class of ensemble methods. It is an ensemble of multiple decision trees, in which each decision tree is a weak learner, but by combining many trees, the model can achieve higher performance. It uses a technique called Bootstrap Aggregation (Bagging), in which the algorithm randomly samples the training data with replacement, creating a new bootstrap sample in the ensemble. It is widely used in regression and classification problems (Lin *et al.*, 2017). The Random Forest model presented in Figure 3 has B number of decision trees and the algorithm performs row sampling with replacement and feature sampling on the dataset X until each decision tree in the network has its portion of the bootstrap data sample. Each decision tree (1 to B) gets trained on the data sample apportioned to it and consequently, each decision tree produces its prediction result (k_1 to k_B) and the results will be aggregated using majority voting (classification tasks) or averaging (regression tasks) to generate a final output (k).

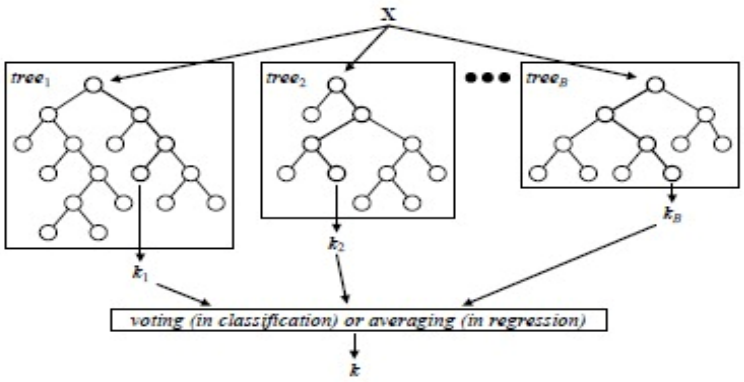

Figure 3: Random Forest (Verikas *et al.*, 2016)

Implementation

The implementation of all four machine learning algorithms was carried out in Python 3.9 on Google Colab. Figure 4 shows some of the imported libraries in Google Colab for implementation of this work, which also contains the code for loading the SCN cases data while the traditional Machine Learning algorithms used to compare the developed system were implemented on a local machine in Anaconda's Jupyter notebook environment with

python 3.9 as shown in Figure 4. Employing Machine Learning for the prediction of Judicial cases involves a series of steps after the needed libraries like Numpy, Pandas, Tensorflow, Keras, Matplotlip, and Sklearn, among others have been imported.

```
import numpy as np
import pandas as pd
import Tensoflow as tf
from sklearn.metrics import classification_report, accuracy_score
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout, Conv1D
from keras.optimizers import SGD
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import LabelEncoder
```

Figure 4: Snippet of Imported Libraries

This prediction process is represented in Figure 5 for clarification and reference.

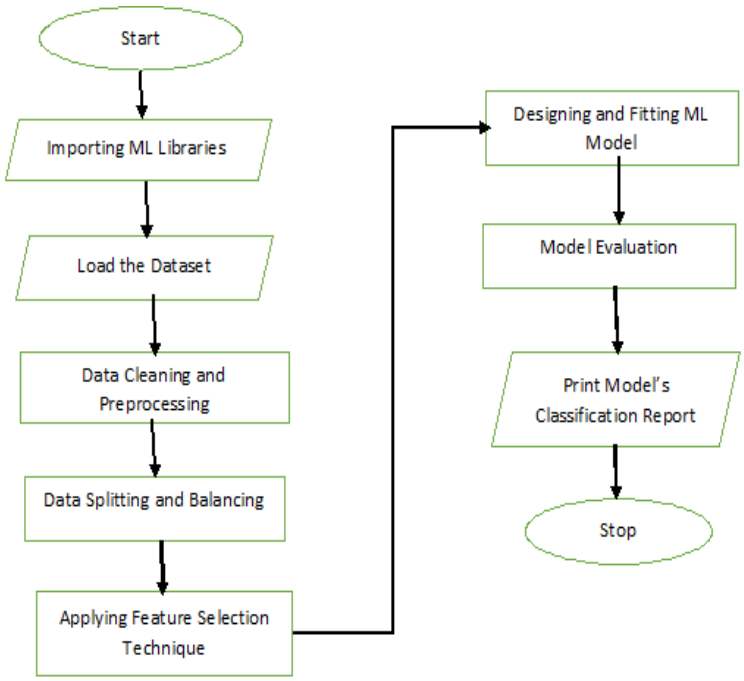

Figure 5: Flowchart of the Model

RESULTS AND DISCUSSION

For the maximum prediction accuracy to be obtained, the four mentioned predictive models were tested using the same dataset. The accuracy, precision, recall, and F1-Score of each predictive model were obtained and the prediction model that gave the best accuracy was noted. Tables 1 to 4 represent the reports that were obtained after testing was carried out on each predictive model. Thus, a comparison was carried out as depicted in Table 5 to obtain the best-performing model.

Table 1: Performance of SVM

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
53	55	35	43

Table 2: Performance of KNN

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
64	63	67	65

Table 3: Performance of Logistic Regression

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
55	55	58	56

Table 4: Performance of Random Forest

Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
72	75	67	70

Table 5: Comparison of the Machine Learning Algorithms

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	53	55	35	43
KNN	64	63	67	65
Logistic Regression	55	55	58	56
Random Forest	72	75	67	70

These four traditional algorithms were graphically compared in Figure 6 to show the distribution of these metrics and show the best algorithm with the best predictive performance based on the evaluation metrics. This implies that Random Forest is the best traditional machine learning algorithm for the prediction of the possibility of acceptance of the cases by the Supreme Court of Nigeria based on the dataset employed in this research. This impressive result obtained by the Random Forest might be a result of its ensemble learning property as many trees were embedded within this algorithm to obtain

the best predictive performance and extensively scrutinize the attributes present in the dataset to learn the best pattern during fitting. Additionally, Random Forest was designed with a deep number of estimators with a good random state, this can also be said to be the secret behind its good predictive performance over the three other traditional machine learning algorithms.

Upon examining each predictive model and assessing its accuracy, the precision values of each model were compared through plotting. Consequently, a clear interpretation emerges, indicating that the predictions made by the Random Forest algorithm are more precise than those of the other predictive models.

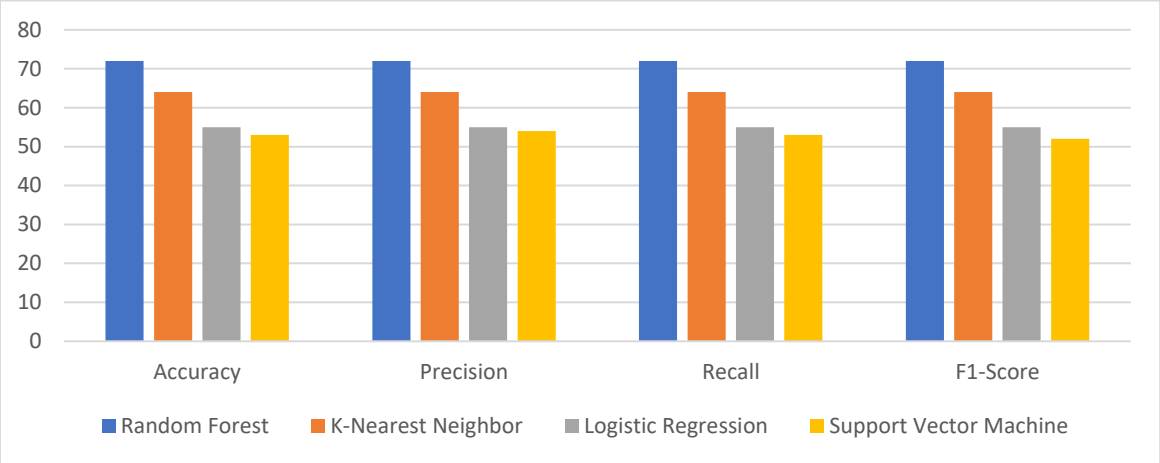

Figure 6: Comparison of Machine Learning Algorithms

Comparison of the Developed System with Existing Studies

Using the SCN dataset, the developed system was compared with other existing systems. The study by Katz *et al.* (2017) was observed to be the closest in performance to the developed system. Table 6 represents the comparison of results obtained when the developed system was compared with existing systems.

Table 6: Existing Systems vs Developed System

S/N	Author	Datasets (Court)	Techniques	Accuracy (%)
1.	Katz *et al*. (2017)	Supreme Court of the United States (SCOTUS)	Random Forest	70.2
2.	Virtucio *et al*. (2018)	Philipine Supreme Court	Random Forest	59
3.	Strickson & De La Iglesia (2020)	United Kingdom Courts	SLP with MLP	59.7
4.	Developed Judicial Prediction System	Supreme Court of Nigeria (SCN)	Random Forest	72

CONCLUSIONS

The widespread impact of Artificial Intelligence (AI) and Machine Learning (ML) on the global perception of computational power in daily life is evident. Through collaborative efforts in Data Science, Computer Science, and Computer Engineering, machines can now adapt to dynamic environments and efficiently solve previously non-computational problems. Developments in AI and ML have further extended the use of computational power across diverse fields, fostering remarkable innovations. Inspired by recent technological advancements, the presented system aims to bridge the gap between individuals and the legal system. In the contemporary era, the legal field permeates every aspect of human existence, regulating life's philosophy and frequently involving citizens with the judicial system. The overwhelming dependence on legal systems, coupled with the pressure on the judiciary due to rapid societal changes, has significantly impacted civilians in terms of compensation and time. The system strives to provide legal assistance by predicting case outcomes with a projected accuracy of 72%, empowering litigants and judicial professionals to make informed decisions in their legal proceedings and contributing to societal betterment through increased understanding and engagement with the legislature.

REFERENCES

Bhilare, P., Parab, N., Soni, N., & Thakur, B. (2019). Predicting outcome of judicial cases and analysis using machine learning. Int Res J Eng Technol (IRJET), 6, 326-330.

Boateng, E. Y., Otoo, J., & Abaye, D. A. (2020). Basic tenets of classification algorithms K-nearest-neighbor, support vector machine, random forest and neural network: a review. Journal of Data Analysis and Information Processing, 8(4), 341-357.

Chalkidis, I., Androutsopoulos, I., and Aletras, N. (2019). Neural judicial prediction system in English [Preprint]. arXiv:1906.02059.

Chen, D.L. (2018). Judicial analytics and the great transformation of American Law. *Artificial Intelligence and Law, 27*, 15 - 42.

Dexter, F., Epstein, R. H., & Marian, A. A. (2022). Case duration prediction and estimating time remaining in ongoing cases. *British journal of anaesthesia*, *128*(5), 751–755. https://doi.org/10.1016/j.bja.2022.02.002

García-Gonzalo, E., Fernández-Muñiz, Z., Garcia Nieto, P. J., Sánchez, A., & Menéndez, M. (2016). Analysis of Hard-Rock Stability for Span Design in Entry-Type Excavations Using Learning Classifiers. Materials, 9(7), 531. https://doi.org/10.3390/ma9070531

Grogger, J., Gupta, S., Ivandic, R., & Kirchmaier, T. (2021). Comparing conventional and machine-learning approaches to risk assessment in domestic abuse cases. Journal of Empirical Legal Studies, 18(1), 90-130.

Katz, D. M., Bommarito, M. J., 2nd, & Blackman, J. (2017). A general approach for predicting the behavior of the Supreme Court of the United States. *PloS one*, *12*(4), e0174698. https://doi.org/10.1371/journal.pone.0174698

Kozodoi, N., Lessmann, S., Papakonstantinou, K., Gatsoulis, Y., & Baesens, B. (2019). A multi-objective approach for profit-driven feature selection in credit scoring. *Decision Support Systems, 120,* 106–117.

Li, J., Cheng, K., Wang, S., Morstatter, F., Trevino, R., Tang, J., & Liu, H. (2016). Feature Selection: A Data Perspective. *ACM Computing Surveys, 50.* https://doi.org/10.1145/3136625

Li, J., Lin, S., Yu, K., & Guo, G. (2022). Quantum K-nearest neighbor classification algorithm based on Hamming distance. *Quantum Information Processing, 21*, 10.1007/s11128-021-03361-0.

Lin, W., Wu, Z., Lin, L., Wen, A., & Li, J. (2017). An Ensemble Random Forest Algorithm for Insurance Big Data Analysis. *IEEE Access*, 5, 16568-16575. https://doi.org/10.1109/CSE-EUC.2017.99.

McCandless, T., and Haupt, S. (2019). The super-turbine wind power conversion paradox: using machine learning to reduce errors caused by Jensen's inequality. *Wind Energy Science, 4*, 343-353. https://doi.org/10.5194/wes-4-343-2019

Medvedeva, M., Üstun, A., Xu, X., Vols, M., & Wieling, M. (2021). Automatic Judgement Forecasting for Pending Applications of the European Court of Human Rights. *ASAIL/LegalAIIA@ICAIL*.

Ngige, O. C., Ayankoya, F. Y., Balogun, J. A., Onuiri, E., Agbonkhese, C., and Sanusi, F. A. (2023). A dataset for predicting Supreme Court judgments in Nigeria. *Data in brief*, *50*, 109483. https://doi.org/10.1016/j.dib.2023.109483

Ranganathan, P., Pramesh, C., & Aggarwal, R. (2017). Common pitfalls in statistical analysis: Logistic regression. *Perspectives in Clinical Research*, 8, 148 - 151. https://doi.org/10.4103/picr.PICR_87_17.

Rani, L. K., Kumar, N., Kumar, J., Kumar, J., Sinha, N. K. (2022). Chapter 6 - Machine learning for soil moisture assessment. In Cognitive Data Science in Sustainable Computing, Deep Learning for Sustainable Agriculture, Academic Press,2022, Pages 143-168, ISBN 9780323852142,https://doi.org/10.1016/B978-0-323-85214-2.00001-X.

Remus, D., & Levy, F. (2017). Can robots be lawyers: Computers, lawyers, and the practice of law. *Geo. J. Legal Ethics*, *30*, 501.

Sari, R. K. (2023, July 21). Prediction types of legal cases in Indonesia using the TF-IDF method and the KNN algorithm. *AIP Conference Proceedings, 2689*(1), 120003. https://doi.org/10.1063/5.0114543

Shi, C., Sourdin, T., & Li, B. (2021). The Smart Court – A New Pathway to Justice in China?. International Journal for Court Administration, 12(1), 4.DOI: https://doi.org/10.36745/ijca.367

Sil, R., & Roy, A. (2021). Machine learning approach for automated legal text classification. International Journal of Computer Information Systems and Industrial Management Applications, 13, 10-10.

Singh, D., & Kaur, K. (2012). Classification of Abnormalities in Brain MRI Images using GLCM, PCA and SVM. *International Journal of Engineering and Advanced Technology (IJEAT), X*(X), 1-8.

Tubishat, M., Idris, N., Shuib, L., Abushariah, M. A. M., & Mirjalili, S. (2020). Improved salp swarm algorithm based on opposition based learning and novel local search algorithm for feature selection. *Expert Systems with Applications, 145*, Article ID 113122.

Verikas, A., Vaiciukynas, E., Gelzinis, A., Parker, J., & Olsson, M. C. (2016). Electromyographic Patterns during Golf Swing: Activation Sequence Profiling and Prediction of Shot

Effectiveness. Sensors, 16(4), 592. https://doi.org/10.3390/s16040592

Virtucio, M. B. L., Aborot, J. A., Abonita, J. K. C., Avinante, R. S., Copino, R. J. B., Neverida, M. P., Osiana, V. O., Peramo, E. C., Syjuco, J. G., & Tan, G. B. A. (2018). Predicting decisions of the Philippine Supreme Court using natural language processing and machine learning. In *2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC)* (Vol. 2, pp. 130-135). IEEE.

Wang, D., Ye, Y., and Kim, D. H. (2019). Predicting U.S. Supreme Court decisions on legal issues with word embeddings and Random Forest. Journal of the Association for Information.

Zhang, C., Zhong, P., Liu, M., Song, Q., Liang, Z., and Wang, X. (2022). Hybrid Metric K-Nearest Neighbor Algorithm and Applications. *Mathematical Problems in Engineering, 2022*, Article ID 8212546, 15 pages. https://doi.org/10.1155/2022/8212546