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Loss of Life Transformer Prediction Based on Stacking Ensemble Improved by Genetic Algorithm

Rosena Shintabella
Master Program of Information System
Universitas Diponegoro
Semarang, Indonesia

Catur Edi Widodo
Department of Physics
Universitas Diponegoro
Semarang, Indonesia

Adi Wibowo
Department of Informatics
Universitas Diponegoro
Semarang, Indonesia

Abstract:- Prediction for loss of life transfomer is very important to ensure the reliability and efficiency of the power system. In this paper, an innovative model is proposed to improve the accuracy of lost of life transfomer prediction using stacking ensembles enhanced with genetic algorithm (GA). The aim is to develop a robust model to estimate the remaining life of a transformer in order to generally increase the reliability of the electrical energy distribution system. This approach involves integrating various machine learning models as a basic model, namely Support Vector Machines (SVM) and K-Nearest Neighbor (KNN). A stacking ensemble framework is then used to combine the predictions of these base models using a meta model namely Logistic Regression (LR). The results show a significant improvement in both transformers using stacking-GA, both TR-A and TR-B, with each prediction evaluation 99% and with a minimal error rate, namely approaching 0.the developed framework presents a promising solution for accurate and reliable transformer life prediction. By integrating a variety of basic models, applying improved stacking layouts using GA, these models offer valuable insights to improve maintenance strategies and system reliability in power grids.

Keywords:- *Genetic Algorithm, Stacking Ensemble, Stacking-GA, Loss of Life Transformer Prediction.*

I. INTRODUCTION

Transformer are critical components in power systems, playing a pivotal role in ensuring the efficient transmission and distribution of electrical energy [1]. Predicting the remaining useful life of transformers is a challenging yet crucial task for maintenance scheduling and reliability optimization. Traditional methods often rely on individual machine learning models, which may not fully capture the complex relationships and patterns within transformer operational data [2].

Classification algorithms such as Support Vector Machine (SVM) and K-nearest Neighbors (KNN) can be used to predicted disturbances in electrical energy distribution networks [3]. Logistic regression produces high accuracy values and low error rates for the case of power generation system predictions[4]. However, the accuracy level also rises when logistic regression combines with other methods. To improve the performance of the machine learning model, a model combining multiple algorithms must be developed, taking into account the strengths and weaknesses of each method. To improve the performance of the machine learning model, a model combining multiple algorithms must be developed, taking into account the strengths and weaknesses of each method.

Ensemble learning techniques have gained attention for their ability to enhance predictive accuracy by combining the strengths of multiple models [5]. Stacking, a popular ensemble method, goes a step further by training a meta-model on the predictions of base models, effectively learning to weigh their outputs optimally [6]. However, the performance of stacking is heavily dependent on the choice and configuration of base models.

Metaheuristic algorithms such as genetic algorithms, have been utilized for identifying the most important parameters for prediction scenarios and can optimize the whole method in prediction [7]. The concept of genetic algorithms that search for the best combination of models and features was also introduced in the field of machine learning to calibrate air quality sensors at low cost. The implementation of genetic algorithms in the feature selection process is expected to improve the performance of the stacking ensemble learning model and produce accurate prediction results [8][9].

This paper proposes an innovative approach to improve the accuracy of loss of life transformer prediction using an ensemble of machine learning models and a genetic algorithm (GA) for model selection and optimization. The goal is to harness the diverse capabilities of various base models and

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intelligently combine their predictions to achieve superior accuracy in estimating the remaining life of transformer.

II. LITERATURE REVIEW

Various methods such as the Support Vector Machine (SVM), K-nearest Neighbors (KNN), and Multinomial Logistic Regression (MLR) algorithms have been experimented with for the prediction of distribution transformer life based on oil test results [1]. MLR exhibits the most effective performance by achieving the highest level of accuracy among these algorithms. Nevertheless, studies also indicate that a reduction in the number of features utilized during testing can enhance the health index of the transformer, subsequently boosting the performance of the employed machine learning model.

Classification of electrical transmission system disturbances can be done using the K-nearest Neighbors algorithm with accurate results. The accuracy level of the KNN algorithm has the best performance with an accuracy of 86% [3]. For the KNN classifier the highest accuracy is maintained constant after using 3 features, but further increase in the number of features is not effective.

The Support Vector Machine (SVM) algorithm is suitable for predicting and categorizing extensive datasets, delivering a high level of accuracy [10]. SVM excels in classifying substantial data volumes, demonstrating an accuracy level of 97.68%. Nonetheless, it exhibits suboptimal Root Mean Square Error (RMSE) results, indicating a need for improvement in the prediction outcomes to ensure precise fault stage detection.

The stacking ensemble method is applicable for classifying and predicting various types of disturbances in power generation systems. In addition to stacking ensemble, ensemble voting can also be employed during the classification process [5]. A combination of the logistic regression algorithm, k-nearest neighbors, and J48 decision tree with the stacking ensemble method achieves the highest accuracy level of 94%. Sensitivity analysis was conducted to validate the proposed ensemble classifier's performance in terms of classification accuracy amidst real-time fluctuations in wind power and event signals with varying levels of noise. The findings indicate that the stacking ensemble method demonstrated the highest level of accuracy.

The stacking ensemble method is applicable for classifying and predicting disturbances in Variable Refrigerant Flow (VRF) systems. Combining base model algorithms such as Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting Machine (GBM), and Back Propagation Neural Network (BPNN) with the meta model Multinomial Logistic Regression (MLR) results in a more optimized model compared to individual model testing [11]. The proposed approach for training and testing data enhances accuracy by 3.9% and 4.02%, respectively, with minimal disparity between the two, demonstrating the model's generalization capability. However, increasing the number of features in the dataset can impact the quality of features, directly influencing the reliability of the prediction model constructed by stacking ensemble methods.

Genetic algorithms are effective for optimizing stacking ensemble learning models, particularly in enhancing predictions for the acidification process in carbonate reservoirs. This optimization aims to increase permeability effectiveness, reduce the drop in wellbore pressure, and minimize acid consumption [12]. The base models utilized in this study include decision tree, support vector machine, and k-nearest neighbor algorithms, with a multi-layer perceptron serving as the meta model. Initially, the stacking ensemble learning achieved an accuracy of 83% but required a considerable amount of time. Following optimization using a genetic algorithm, the runtime of the ensemble model improved by 99%, and the accuracy rate increased by 10%.

Genetic algorithms are effective for optimizing stacking ensemble machine learning models, particularly in the context of enhancing predictions for road dust in urban areas [13]. The base models employed in this study include the k-nearest neighbor algorithm, random forest, and light gradient-boosting machine, with multivariate linear regression serving as the meta model. Utilizing genetic algorithms for configuring stacking ensemble models yields optimal outcomes, along with robust validation across spatial and temporal dimensions. The genetic algorithm, particularly in feature selection, conducts a purposeful global search to identify the most suitable learning model and optimal hybrid predictor for completing the stacking ensemble framework.

Genetic algorithms are valuable for enhancing machine learning algorithms based on ensemble bagging, particularly in the context of predicting flood vulnerability in Iraq's Sulaymaniyah province. This research utilized four machine learning algorithms: random forest (RF), bagging, RF-genetic algorithm, and bagging-genetic algorithm [14]. The findings indicate that all proposed models exhibit high prediction accuracy, with the bagging-genetic algorithm performing slightly better than the RF-genetic algorithm. Moreover, the hybrid approach with the genetic algorithm outperforms individual algorithms. As per the ROC index, the bagging-genetic algorithm model (AUC = 0.935) demonstrates the highest accuracy in modeling flood vulnerability, followed by the RF-genetic algorithm.

III. METHOD

The research method used has a research flow with stages of dataset, optimization, stacking ensemble level 0, stacking ensemble level 1 and evaluation. An overview of the stages used in this research is shown in Fig. 1.

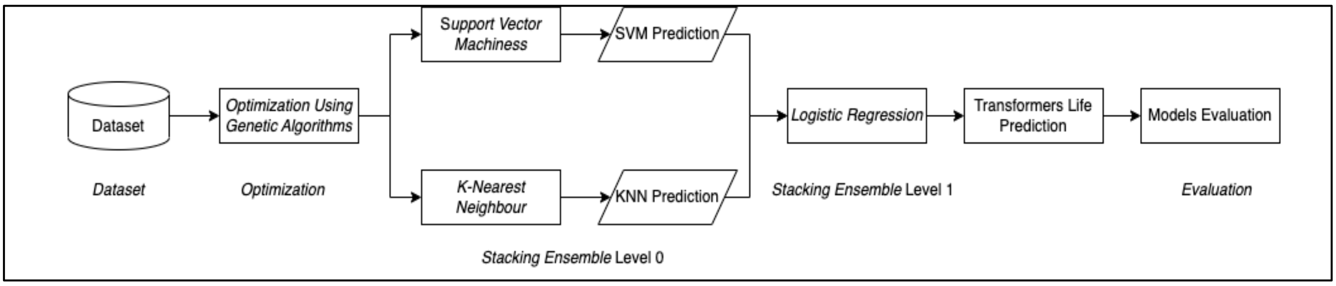

Fig. 1. Research Flow

A. Dataset

The data used is data on electrical distribution system disturbances at a feeder for 2 year starting from January 2021 to December 2023. This research uses 4 input parameters, namely data on current in the R phase, S phase, T phase and temperature. With a label indicating the remaining life of the transformer as determined by calculating the transformers life. In this study, two transformers with varying years of service and the specifications listed in table 1 were used.iteria that follow.

Table 1 Transformers Specification

Transformer Code	Capacity	Year	Year of Operation
TR-A	100 kVA	2017	5-6 Years
TR-B	150 kVA	2018	4-5 Years

There are 2 stages of data preprocessing, namely data cleaning and data separation. The data cleaning stage aims to identify, correct, or remove errors, discrepancies, and anomalies in the data. In this research, data cleaning was carried out by deleting data containing NA's in a column. The next stage is the data separation process. In this process the 730 dataset will be divided into 2, namely 80% of 584 data will become training data and 20% of 146 data will become test data [15][16].

B. Optimization

The optimization process using a genetic algorithm comprises five stages: initialization population, fitness function evaluation, selection of parental genes, crossover, and mutation. The population initialization stage begins by executing a function to create a random population based on input data variables, specifically currents in R, S, T, and temperature. Following the initialization of the random population, the subsequent step involves running a fitness function to identify the best parent genes. If the fitness value derived from the population is satisfactory, the process concludes. However, if the results fall below a 70% accuracy threshold, the process proceeds to the stages of selecting parental genes, crossover, and mutation. The selection of optimal parental genes is determined by the 'n-parent' parameter, with 32 'n-parents' being utilized in this study. Subsequently, the genes undergo crossover and mutation functions. Crossover occurs 16 times with 2 parents involved in each process. The mutation rate in this research was set at 1%.

C. Stacking Ensemble Level 0

The stacking ensemble method has two levels, level 0 and level 1. Level 0 refers to the independent training of base models until each base model produces a prediction. The first model used for base models is the Support Vector Machine (SVM). In this research, SVM is used as a support vector classifier with the One Vs All method to classify cases with multinomial data. K-Nearest Neighbor (KNN) is the second model deployed for the base model. In this research, a distance with a K value of 7 will be calculated using Euclidean distance.

D. Stacking Ensemble Level 1

Stacking ensemble learning involves the combination of base models with meta models to achieve optimal prediction outcomes. In the initial stage of stacking ensemble at level 0, the data undergoes training using independent base models, specifically SVM and KNN. The prediction outputs from the level 0 base models will be used as input for the level 1 stacking ensemble learning. Multinomial Logistic Regression used for meta model in level 1 for multinomial dataset case. Predictions with combination or ensemble results with stacking ensemble models will be the output of the basic models SVM, KNN, and logistic regression meta models combined.Fig. 2 is a illustrates for stacking ensemble configuration.

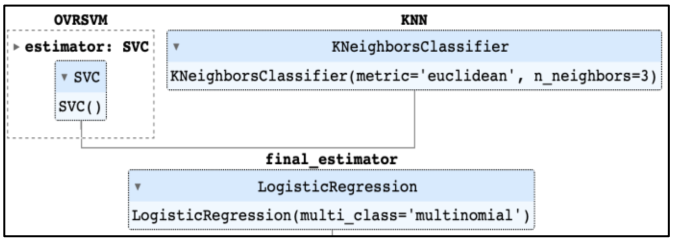

Fig. 2. Stacking Ensemble Configuration

E. Evaluation

A matrix is a measure or indicator used to measure the performance of a machine learning model. This can determine whether a machine learning model is working well or needs to be improved. Matrices that are often used in machine learning evaluations for predictions include accuracy, precision, recall, f1-score, Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

Accuracy measures the percentage of correct predictions out of all predictions Accuracy values range between 0 and 1, with 1 indicating a perfect prediction and 0 indicating a completely incorrect prediction. In the formula TP = true

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positive, TN = true negative, FP = false positive and FN = false negative.

$$\text{Accuracy} = (TP+TN)/(TP+FP+FN+TN) \quad (1)$$

Precision is the ratio of true positive predictions compared to the overall positive predicted results. Precision measures the ratio of correct positive predictions out of all positive predictions. Precision provides information about how often a machine learning model makes correct positive predictions. The precision value ranges between 0 and 1.

$$\text{Precision} = TP/(TP+FP) \quad (2)$$

Recall is the ratio of true positive predictions compared to the total number of true positive data. Recall measures the ratio of true positive data found to all positive data. Recall provides information about how well the machine learning model found all positive data.

$$\text{Recall} = TP/(TP+FN) \quad (3)$$

F1 score is a measure of balance between precision and recall, with a high value indicating a good balance between the two metrics. The best F1-Score value is 1 and the worst value is 0. In representation, if the F1-Score has a good score, it indicates that our classification model has good precision and recall.

$$\text{F1 Score} = 2(\text{Recall x Precission}/(\text{Recall+precision}) \quad (4)$$

Mean Squared Error (MSE) is used to measure the average square of the difference between the prediction and the target. MSE can also be used to estimate the inaccuracy of the target machine model. in the MSE formula y' = predicted value, y = actual value and n = data.

$$\text{MSE} = \sum \frac{(y' - y)^2}{n} \quad (5)$$

Root Mean Square Error (RMSE) is the sum of the squared errors or the difference between the actual value and the predetermined predicted value. RMSE evaluation is calculated based on the average value of the sum of the squared errors between the forecast results and the actual value. The value is used to measure the amount of error produced by the prediction model. The value is used to measure the amount of error produced by the prediction model.

$$\text{RMSE} = \sqrt{\sum \frac{(y' - y)^2}{n}} \quad (6)$$

IV. RESULT AND DISCUSSION

This research uses input data from transformer current and temperature data in the electricity distribution sector in Indonesia. Predictions in this research use an algorithm with a stacking ensemble method combined with a genetic algorithm. The machine learning evaluation results will be interesting to compare the results of individual ML models, stacking ensemble, individual-GA, and Stacking-GA.

A. Individual and Stacking Ensemble Machine Learning Models

The first stage in developing a model is learning about the results of the model's design that will be deployed. In this research, the machine learning model and stacking ensemble were initially evaluations. After received the evaluation results, the next step is to improve the model performance using a genetic algorithm. The comparison results of individual and stacking ensemble machine learning evaluations are shown in fig. 3.

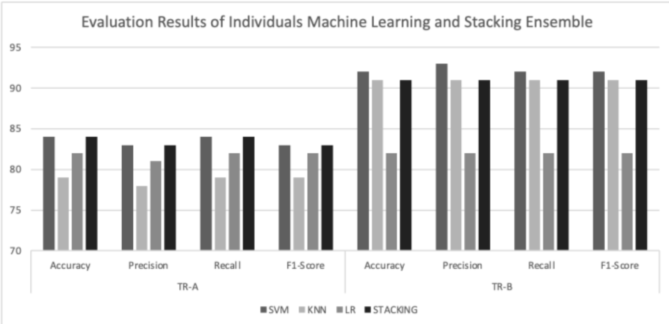

Fig. 3. Evaluation Results of Individuals Machine Learning and Stacking Ensemble

The four selected models show different results when the model is used to predict the age of an electric transformer using GA, which will produce an estimate of the life of the transformer so that it can work according to its capacity. SVM and Stacking Ensemble produce the best average on the TR-A transformer with the same for accuracy of 84%, precision of 83%, recall of 84% and f1-score of 83%. Meanwhile, on the TR-B transformer, SVM produces the best average with 92% accuracy, 93% precision, 92% recall and 92% f1-score. Due to variations in transformer specifications and parameter value ranges, the two datasets produce different results.

The most optimal output prediction should produce an evaluation average of 1 because it will not meet realistic assumptions when calculating the number of disturbances that cause reduced transformer life. Another thing that needs to be noted is that the output used in this research does not contain things that do not affect the life of the transformer. The temperature and current of the R, S, and T phases are important variables in maintaining transformer quality. In addition, because unsuitable transformer oil can cause temperature instability, it is important to consider the quality of the oil. Careful consideration of context is critical to making appropriate decisions in prediction cases.

B. Implementation of Genetic Algorithm

The application of the algorithm in feature selection begins by running the random population initialization function. The performance of hybrid models can be influenced by various parameters such as population size, outcrossing and mutation rates. In this research, the following settings were implemented with the population size of the genetic algorithm being 146, and the best 32 parents were

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selected for each run, with random crossovers among individual input columns and a mutation rate of 1%. The comparison results of model non improved and model with improved by genetic algorithm are shown in fig. 4.

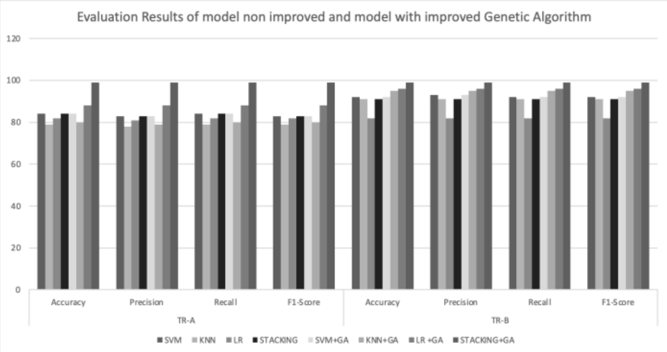

Fig. 4. Evaluation Results of Non-Improved Models and Models with Improved Genetic Algorithm

For the TR-01 transformer, using a combination of the KNN-GA, LR-GA and stacking-GA algorithms shows that the average evaluation achieves the best results. In stacking-GA, the average improvement in evaluation increases by 15%. The best results were shown by the stacking-GA model with accuracy, precision, recall and f1-score each of 99%. However, the performance of the genetic algorithm on the SVM model has no effect, as can be seen from the accuracy, precision, recall and f1-score showing the same results as the SVM model without the genetic algorithm.

For the TR-02 transformer, using a combination of the KNN-GA, LR-GA and stacking-GA algorithms shows that the average evaluation achieves the best results. In stacking-GA, the average improvement in evaluation increases by 8%. The best results were shown by the stacking-GA model with accuracy, precision, recall and f1-score each of 99%. However, the performance of the genetic algorithm on the SVM model has no effect, as can be seen from the accuracy, precision, recall and f1-score showing the same results as the SVM model without the genetic algorithm. From the evaluation results on both transformers, it can be concluded that the genetic algorithm can improve the stacking ensemble performance in the prediction case.

C. Evaluation of MSE and RMSE

In the case of predictions, a further evaluation is required to determine the accuracy of the implemented prediction model. Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are important metrics in the context of prediction tasks. The comparison results of evaluation using MSE and RMSE for transformer TR-A and TR-B are shown in fig. 5.

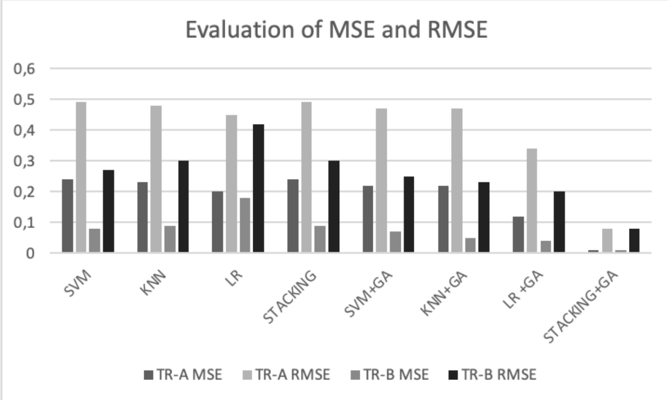

Fig. 5. Evaluation of MSE and RMSE

Both metrics provide insight into the accuracy and suitability of predictive models. The MSE and RMSE values are said to be good if they are close to 0. Figure 4 is the result of a comparison of the MSE and RMSE values in research on electrical transformer life prediction. In the TR-01 and TR-02 datasets, the hybrid method with the genetic algorithm reaches a value close to 0, which means the hybrid method is more accurate for prediction cases than the individual methods. The best results were shown by the hybrid stacking-GA model.

D. Comparison of Prediction Result

In the case of predictions, a further evaluation is required to determine the accuracy of the implemented prediction model. Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are important metrics in the context of prediction tasks. There are 8 prediction models built with 3 individual ML models, stacking ensemble model, 3 ML-GA models and stacking-GA. The stacking-GA model is proven to be the most suitable to individual models with an average best value in prediction loss of life transformer with TR-A and TR-B. Optimized output predictions are more accurate because there are minimal errors, which means the method is accurate for the electrical transformer life prediction model.

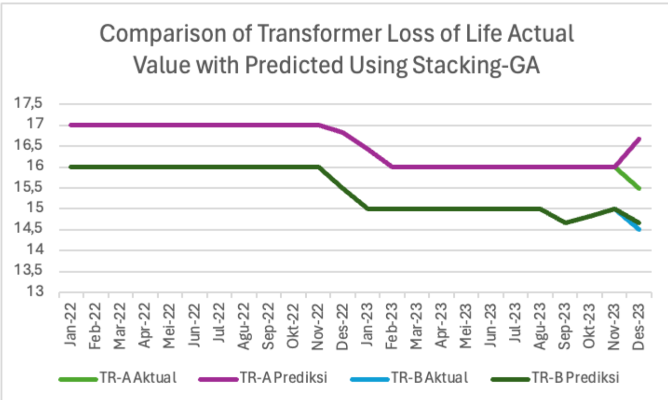

Fig. 6. Illustration of Comparison of Trasformers Loss of Life

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Figure 6 is an illustration of the comparison of the actual value with the predicted results stacking-GA. In the illustration, there is no significant difference because the good average value is close to perfect, so there is no difference between the actual value and the prediction. The best average evaluation of the developed model, which has an error.

V. CONLUSION

The application of genetic algorithms to improve the performance of stacking ensemble models shows increased accuracy and minimal errors compared to the individual model approach. Through experimentation and validation, it was found that the Stacking-GA model performed better than individual models with an average increase in validation results reaching 15% and errors approaching 0. The Stacking ensemble method allows the aggregation of diverse basic models, each of which contributes to its own advantages. - each basic model into complex relationships in transformer life prediction problems. Meanwhile, the use of GA facilitates the adjustment of model parameters, thereby improving the overall model performance and thereby improving the performance of the stacking ensemble model. The developed model promises practical implementation in electric power distribution systems, where accurate loss of life transformer predictions can result in optimal maintenance schedules, reduce downtime, and increase overall system reliability.

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