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Model Prediction Using Artificial Neural Network (ANN) to Strengthen Diagnostic Analysis of Diabetes Melitus

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Abstract **-** The incidence of Diabetes Mellitus (DM) is one of the urgent and increasing health issues every year. Hence, this condition requires high urgency to be handled. The research aimed to develop a prediction model for DM that could be used in general for the purpose of diagnostic analysis of DM cases against suspected individuals. The dataset was sourced from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK), which had closely related parameters in diagnostic analysis without favoring certain groups. The targeted contribution was the result of a new prediction model that was specifically tested on the dataset using the Artificial Neural Network (ANN) algorithm. This model was developed through a baseline model that was tested and improved in performance through hyperparameter cross-validation therapy and L1 regularization. The formation of the model architecture through experiments to adjust the conditions of hidden layers and neurons in several configurations results in a model architecture with 8 input parameters. It contains 3 hidden layers with a total of 14, 20, and 26 neurons, with the ReLU activation function on each hidden layer and the Sigmoid activation function on the output part. The second test is carried out on a hyperparameter configuration. It produces maximum performance with a k-fold value of 10 and L1 regularization of 0.0001. The model performance results obtain an accuracy value of 0.947, precision of 0.895, recall of 0.914, and model loss of 0.215.

Keywords**:** model prediction, Artificial Neural Network (ANN), diagnostic analysis, diabetes mellitus

I. INTRODUCTION

A long-term metabolic condition known as Diabetes Mellitus (DM) is characterized by increased blood sugar levels. DM can cause major health problems such as kidney failure, heart disease, and blindness (Izzo et al., 2021). The disease affects millions of people worldwide, and its prevalence is increasing rapidly, especially in developing countries (Piko et al., 2021).

Machine learning has recently attracted more attention in the medical industry, especially for intelligent diagnosis. As a result, it has been widely applied to smart diabetes diagnosis (Richens et al., 2020). Similarly, in the ongoing problem of DM disease, various machine learning algorithms have been used to predict DM. This algorithm includes a Decision Tree (Thotad et al., 2022), Random Forest (Mustafa et al., 2023), Support Vector Machine (SVM) (Zaman et al., 2022), and Neural Network (Sharma & Shah, 2021). Machine learning models can aid in diagnosis, classification, and treatment planning by evaluating and mining patient data from people with diabetes. Researchers manage and use machine learning in diabetes diagnosis in the hope of managing and treating diabetes.

The research aims to build a more general and unbiased prediction model for diagnostic analysis from a particular group or gender using the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) dataset. The selection of datasets does not support the PIMA Indian Diabetes Dataset, but the data sources in NIDDK correlate very well with the research goals. Pima Indians Diabetes Dataset is a single data set for the PIMA Indian female ethnic group as evidenced by the pregnancies parameter in

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the dataset parameter set (Mustofa et al., 2023).

The final data set has various parameters such as glucose, cholesterol, High-Density Lipoprotein (HDL) cholesterol, Body Mass Index (BMI), age, and others that are relevant in the diagnostic analysis of the occurrence of DM cases in patients. This diversity indicates the level of complex and non-linear relationships, where changes in one variable can cause disproportionate changes in other variables. The non-linear condition of datasets is very ideal for machine learning algorithms such as Artificial Neural Network (ANN) with its ability to handle non-linear and complex data (Alifiah et al., 2023). ANN can accept very complex patterns and feature interactions through the existence of each layer on the hidden layer. It makes ANN able to learn more deeply from data that has high complexity (Prasetyo, 2023).

It is necessary to reason and trace all forms of technological renewal efforts in the case of DM predictions that have been carried out in previous times to clarify this direction and goal. The researchers highlight parallel research on the dataset used. In the last three years, researchers made many contributions to come up with predictive models to shed light on DM health problems.

In previous research, all parameters are involved in the case prediction process based on the K-Nearest Neighbor (KNN) algorithm with k-fold (k=3), and the test uses 20% of the total case data where KNN manages to get an accuracy level of 93.58% (Chandra & Nasien, 2023). In other research on similar datasets, it selects parameters by eliminating unnecessary parameters so that cholesterol, glucose, HDL cholesterol, age, gender, weight, systolic Blood Pressure (BP), diastolic Blood Pressure (BP), diabetes are selected (Benmansour, 2021). Another previous research classifies diabetes cases by applying the Naive Bayes algorithm to 40% of the data on the dataset and a scaling process that aims to normalize the data. The performance results of the Naive Bayes algorithm in the case classification process give an accuracy value of 92.3% at the training stage and 91.6% during the algorithm testing period (Nurul Anisa & Jumanto, 2022). Still using similar datasets, the previous researchers carry out them using the KNN algorithm (Prasetyo & Laksana, 2022). The model is built using all parameters in the dataset by applying cross-validation techniques to optimize the existing KNN model. The performance of the KNN model produces an accuracy value of 94% and receives improvements during the model training process through the existence of cross-validation, which is carried out as many as fivefold. Hence, the model experiences a decrease in overfitting conditions.

On the other hand, the application of technology in the case of DM prediction using a machine learning approach, especially with the ANN algorithm, has also been further researched. The research is conducted on the PIMA Indians diabetes dataset by comparing the algorithm of the Neural Network and SVM (Dewi et al., 2023). The testing process is carried out by applying the cross-validation division technique of ten folds. The ANN model is built using one hidden layer with seven neurons combined with the conditions of the learning rate and momentum parameters. In the learning range condition, it is set with a value of 0.01 to 0.99 and steps as much as five with a linear scale. In the momentum part, it uses a range of 0.01 to 0.9 with the same steps and scale. The accuracy obtained by ANN in this case is 77.60%. Efforts to predict DM cases involving the ANN algorithm and six machine learning classification algorithms are carried out on the PIMA and Omani population datasets. The ANN algorithm obtains the third-highest accuracy score after the Decision Tree and Random Forest algorithms, with an ANN accuracy score of 97.3% (Al Sadi & Balachandran, 2023). In another effort that uses the goal of predicting DM disease by using deep learning models, it compares the ANN algorithm against the PIMA data set. The performance value generated by ANN compared to other algorithms is at the bottom with an accuracy value of 68% (Naseem et al., 2022).

There have been many research contributions to the prediction of DM disease in the last three years. However, based on both sides of the research presented, there is a gap in the research case on the dataset used (Benmansour, 2021). There is still little effort made using this dataset, especially using the ANN algorithm proposed in the research. In addition, research on the purpose of predicting DM by involving the ANN algorithm has been carried out quite a lot. However, those are based on the PIMA one-sided dataset that describes the condition regarding the majority of data cases of women, as has been done in previous studies.

Efforts to present novelty in DM are carried out by applying the ANN algorithm to the set of datasets that have been agreed upon in the research to produce a more general prediction model of DM cases using relevant parameters in the diagnostic analysis of the occurrence of DM cases in a patient. The stages carried out in the research include determination, dataset collection, and selection of parameters for the dataset. Then, they are followed by analyzing the feasibility of the dataset by detecting and deleting outlier data and equalizing the data distribution in the dataset. In the process of building the model, experiments are carried out to determine the ANN architecture and hyperparameters to be used. Finally, the model is evaluated using the confusion matrix tables, accuracy, precision, recall, F1-score, Receiver Operating Characteristic (ROC), and model loss values of the prediction model.

II. METHODS

The research is carried out by arranging several stages. The overall research flow is depicted in Figure 1. The first stage begins with determining an appropriate dataset for the research objectives. It is to produce a model that can be used in diagnostic analysis of all individuals suspected of having a chance of suffering from DM disease. The dataset represents

the parameters needed for the research objectives (Benmansour, 2021).

The stage of selecting the main parameters used in the research refers to the previous research (Nurul Anisa & Jumanto, 2022). The dataset has 390 diabetes case data divided into two classes: diabetes and non-diabetes. The data distribution for each class is 60 for diabetes and 330 for non-diabetes. The difference in the research occurs in the use of human body weight parameters. Similar research considers using the weight parameter, while the research proposes to consider using the BMI parameter, which is a combination of two other parameters, height and weight. It can both represent a person's body weight. All parameters used in building the model are prepared as many as eight apart from the prediction parameters, including cholesterol, glucose, HDL cholesterol, age, gender, BMI, systolic BP, and diastolic BP.

Through the readiness analysis stage, the dataset is prepared for the modeling process at the next stage. Preparing datasets that are ready to be used in modeling is a challenge in machine learning-based research. The need for clean and adequate data is a major challenge that is very often faced in many research efforts. The initial step of dataset analysis is carried out by detecting outlier data using the Q1, Q2, and Q3 data with the quartile calculation method.

Interquartile Range (IQR) is a measure used in statistics to describe the distribution of data. Equation (1) provides an IQR calculation formula. Quartile data analysis is carried out by dividing the data set into several equal parts. The process of dividing the data into several parts provides convenience in seeing the position of data values in the distribution of quartile data (Sihombing et al., 2023; Maulana et al., 2022). The data can be said to be outlier data if the observation value is greater than $Q3 + 1.5 * IQR$ (Equation 2) or less than $Q1 - 1.5 * IQR$ (Equation 3). The results of the outlier analysis on the dataset on all parameters of the prediction model are shown in Table 1.

$$IQR = Q3 - Q1, \quad (1)$$

$$upper = Q3 + 1.5 \times IQR, \quad (2)$$

$$lower = Q1 + 1.5 \times IQR. \quad (3)$$

From the results of outlier detection using a quartile approach placed on the Data Outlier Quartile (DOQ) column, the restriction method is used to handle the existence of data identified as outliers. Outlier data are handled through a throttling process that allows the transformation of extrinsic values into more reasonable values while minimizing data loss. The purpose of the capping method is to eliminate the existence of outliers by maintaining a consistent amount of data in the dataset so that the integrity of the data is not erased. The condition of the actual amount of data in each parameter is in the Row Data (RD) column. Then, the final condition of the data after the capping process is carried out is shown in the After Capping (AC) column (Feng et al., 2023). The results of the application of the detection method and the outlier removal process are highlighted in the Remove

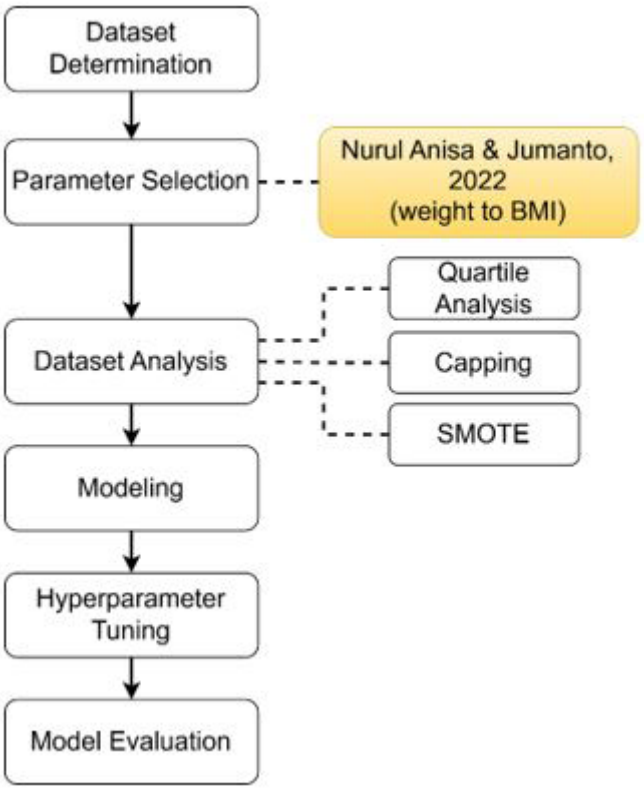

Figure 1 Research Flow

Outlier Capping (ROC) column in Table 1.

The analysis continues by looking at the balance of class distribution on the dataset. The dataset is depicted with an unbalanced data distribution from two existing classes: diabetes (1) and non-diabetes (0). The researchers seek to improve the data imbalance in both classes by using the popular Synthetic Minority Oversampling TEchnique (SMOTE) technique in this case through the upsampling process (Syukron et al., 2023). SMOTE works by changing the dataset by increasing the amount of data in the minority class through a synthetic data formation process. It is based on the calculation of the number of nearest neighbors. The closest neighbors are determined based on the Euclidean distance between the two data points (Halim & Azmi, 2023). The process of forming synthetic data from SMOTE is carried out using Equation (4).

$$x_{syn} = x_i + (x_{knn} - x_i) \times \beta, i = 1, \ldots, n \quad (4)$$

The purpose of increasing the amount of data on minority classes is to improve the performance of the prediction model and reduce the overfitting condition which is a weakness of the oversampling technique. Minority class (1) is improved by a percentage of 75% of the total case data in class (0). The final result of the SMOTE dataset process increases the number of case data in class (1) by 247 and class (0) by 330 (see Figure 2).

In the modeling stage, the need for experimental planning and determination of the model architecture is determined at the beginning to produce the basic model of the research. The basic model is explored by conducting empirical experiments by determining the number of layers and neurons hidden within them in several experiments that the researchers call the internal parameters of the model. In general, choosing the conditions of the hidden layer and the number of neurons is a process done by trial and error to find the best network configuration (Nguyen et al., 2021).

Table 1 Outlier Analysis and Outlier Cleaning Results

Parameters	RD	DOQ	ROC	AC
Cholesterol	390	11	0	390
Glucose	390	50	0	390
HDL_chol	390	13	0	390
Age	390	0	0	390
Gender	390	0	0	390
BMI	390	8	0	390
Systolic_BP	390	12	0	390
Diastolic_BP	390	13	0	390
Total		**107**	**0**	

Note: HDL_chol = High-Density Lipoprotein (HDL) Cholesterol, BMI = Body Mass Index, Systolic_BP = Systolic Blood Pressure, Diastolic_BP = Diastolic Blood Pressure, RD = Row Data, AC = After Capping, DOQ = Data Outlier Quartile, and ROC = Remove Outlier Capping.

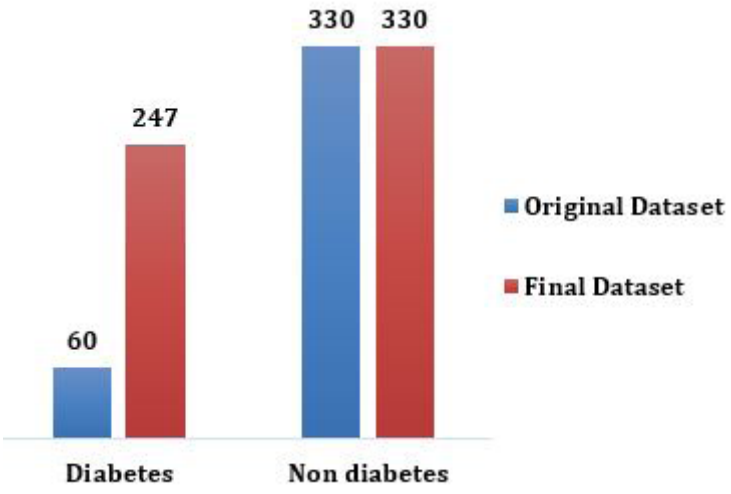

Figure 2 Comparison of Original Dataset with Synthetic Minority Oversampling TEchnique (SMOTE) Results

The experimental scenario is carried out by nine experiments with changes in hidden layers 1 to 3, with a proportion of 80% (461 data) and 20% (116 data) for training and testing model data, respectively. Scenario details are shown in Table 2.

In architectural modelling, it involves selecting the activation function of the Rectified Linear Unit (ReLU) to function as an active function in the hidden layer. ReLU is an activation function used to normalize the values generated by the layer. ReLU means setting a limit at zero that is $x < 0$ then the value of $x = 0$, and $x > 0$ then $x = x$ (Vijayalakshmi & Venkatachalapathy, 2019). The function of Equation (5) is the activation of ReLU. The output of the model is set using the Sigmoid activation function. Sigmoid functions are non-linear functions commonly used in artificial neural networks. This function maps the input value to a value between 0 and 1, making it ideal for representing the probability or level of activation of a neuron (Handayani et al., 2022). The function of Equation (6) is the activation of Sigmoid.

$$f(x) = \max(x, 0), \quad (5)$$

$$f(x) = \frac{1}{1+e^{-x}}. \quad (6)$$

Next, hyperparameters are external controls for machine learning models that determine how the model behaves during training (Michelucci, 2018). The researchers involve hyperparameter cross-validation in improving the consistency, accuracy, and performance of the baseline model. The dataset is divided using the k-fold cross-validation approach. Then, the researchers use the L1 regularization technique (Lasso) to prevent overfitting conditions. Overfitting is a condition caused by the presence of dataset sizes that are not so large or varied during the model training process (Anil & Singh, 2023). L1 regularization works by converting some coefficient values into zero values by estimating the middle value of the data to avoid overfitting (Li, 2023). The trial of using both hyperparameters against the baseline model is evaluated using the general machine learning evaluation method. The details of the hyperparameter configuration are shown in Table 3.

The model evaluation stage is carried out by evaluating the baseline model by looking for the best model based on performance assessment seen from the confusion matrix table, accuracy, precision, recall, and model loss value. The loss function of the model functions to calculate the model performance estimates the difference between how much the predicted value is estimated from the actual predicted value (Kadhim et al., 2023). The model loss function helps to determine efficiency by evaluating the loss value of the model. It gets better if it has a value close to zero. If the condition is the opposite, the model is not suitable and requires improvement of internal or external parameters (Anil & Singh, 2023).

Table 2 Artificial Neural Network (ANN) Architecture Model Experiment Scenario

Scenario	Hidden Layer	Neurons
1		4
2	1	6
3		8
4		6 : 10
5	2	8 : 12
6		10 : 14
7		10 : 16 : 22
8	3	12 : 18 : 24
9		14 : 20 : 26

Table 3 Hyperparameter Model Configuration

Parameter	Value Model
K-fold	5, 10, 15
L1 Regularization	0.0001, 0.001, 0.01

III. RESULTS AND DISCUSSIONS

The research has a very close proximity to the previous research conducted by Nurul Anisa & Jumanto (2022) based on the use of the number and type of parameters in predicting DM cases. The research successfully provides a new model for DM case prediction by using the ANN algorithm approach on the dataset used. From the results of the experiment in Table 2, the researchers highlight the best-performing models outlined in Table 4. It has training accuracy (ATr), testing accuracy (ATs), precision (Prec), recall, and model loss values. In terms of model accuracy during the model training and testing process, it finds that in the nine scenarios carried out, the best ANN architecture performance is in scenario 9. The details of the scenarios performed from all evaluation parameters are displayed in Table 4 consecutively with values of 0.88 (ATr), 0.91 (ATs), 0.85 (precision), and 0.94 (recall). The smallest model loss value of 0.24 is generated using the ANN prediction model architecture with three hidden layers, each using the neurons of 14, 20, and 26.

The researchers focus on the model loss value in the architectural model in scenario 9, which has the smallest model loss value in the entire experiment. However, in terms of accuracy, the architecture testing stage in scenario 9 assesses the accuracy equivalent to several other scenarios, such as scenarios 2, 5, and 8, which produce a testing accuracy value of 0.91 or 91%. However, the model loss value provides another view of the performance of the ANN prediction model, where the smaller the model loss value obtained in the ANN prediction model architecture shows a more efficient model because it has a prediction value that is close to the actual condition. It is the basic point used in determining the baseline model to be passed on to improve its performance using two hyperparameters based on Table 3.

Next, the research enters the part of applying hyperparameters to the baseline model that has been determined. The experiment is carried out nine times based on the combination of the two hyperparameters that have been defined. Details of the results of the hyperparameter implementation are presented in Table 5. Based on the results in Table 5, the researchers find that the best configuration of the hyperparameter lies in

Table 4 Results of Artificial Neural Network (ANN) Architecture Experiment

Scenario	ATr	ATs	Prec	Recall	Loss
1	0.79	0.88	0.87	0.83	0.30
2	0.83	0.91	0.87	0.87	0.28
3	0.83	0.90	0.87	0.85	0.28
4	0.85	0.88	0.78	0.98	0.25
5	0.84	0.91	0.86	0.89	0.27
6	0.86	0.89	0.87	0.87	0.28
7	0.89	0.84	0.75	0.89	0.28
8	0.89	0.91	0.83	0.96	0.25
9	0.88	0.91	0.85	0.94	0.24

Note: training accuracy (ATr), testing accuracy (ATs), and precision (Prec).

Table 5 Results of Hyperparameter Experiment with Modal Baseline

Hyperparameter		ATr	ATs	Prec	Recall	Loss
K-Fold	L1					
5	0.0001	0.88	0.86	0.77	0.94	0.34
	0.001	0.95	0.93	0.85	0.96	0.32
	0.01	0.85	0.91	0.84	0.91	0.68
10	0.0001	0.90	0.95	0.90	0.91	0.21
	0.001	0.90	0.89	0.83	0.96	0.31
	0.01	0.88	0.88	0.81	0.94	0.49
15	0.0001	0.91	0.89	0.86	0.91	0.24
	0.001	0.91	0.92	0.39	1.00	0.33
	0.01	0.86	0.93	0.88	0.94	0.58

Note: training accuracy (ATr), testing accuracy (ATs), and precision (Prec).

using a hyperparameter with k-fold (k=10). Then, the L1 value is applied at 0.0001. There is an improvement in all evaluation parameters compared to the previous baseline model. The performance improvement results are shown in Figure 3.

The use of hyperparameters improves the performance of the baseline model by evaluating the values of ATr, ATs, Prec, recall, and model loss (see Figure 3). The ATr value increases from 0.877 to 0.898. Meanwhile, ATs increases from 0.913 to 0.947. In the model precision value, it changes from 0.846 to 0.895. Meanwhile, there is a slight decrease in the recall value from 0.936 to 0.914. Finally, the model loss value becomes even better by decreasing to 0.215 from the original 0.241. The achievement of a model loss value of 0.215 by applying hyperparameters has an impact on changes and benefits to the performance of the ANN prediction model. It reduces the overfitting condition experienced by the model due to the lack of data or variation in the dataset used. It can also be seen through the comparison of the model's ability to make actual predictions in the confusion matrix table presented in Figure 4.

The model with the hyperparameter application is a model proposed from the research result conducted. It has increased the prediction of True Negative (TN) from 60 to 64 data. However, True Positive (TP) has decreased to a value of 43 from 46. Meanwhile, False Negative (FN) and False Positives (FP) are balanced with values of 5 and 4 respectively. These values have increased more compared to the previous condition values of 9 and 1. It is noted that the FP value has increased in the basic model. The increase in the FP value shows the model's predictive ability in diabetes (non-diabetes) cases. The ideal prediction shows good ability when the TP value gets bigger, and the FP becomes smaller.

The research is successfully completed with a final report explaining the comparison of the baseline model and the model proposed as the final model to predict DM based on diagnostic analysis. It provides good changes. The final model with hyperparameters can improve the performance of the proposed prediction model.

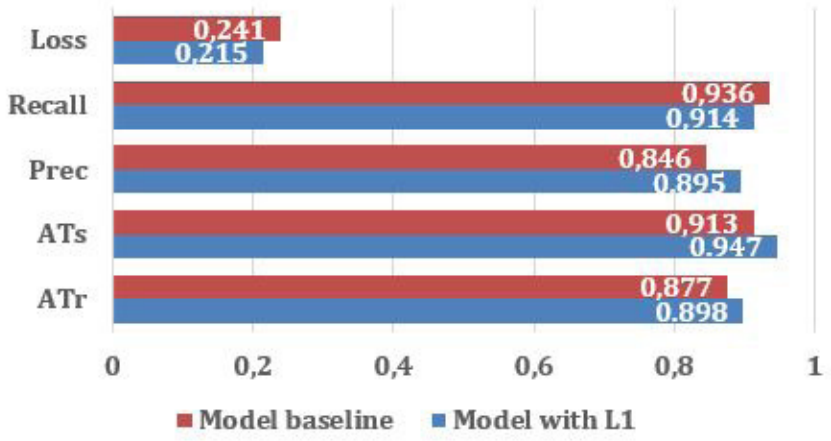

Figure 3 Comparison of Model Performance Improvement

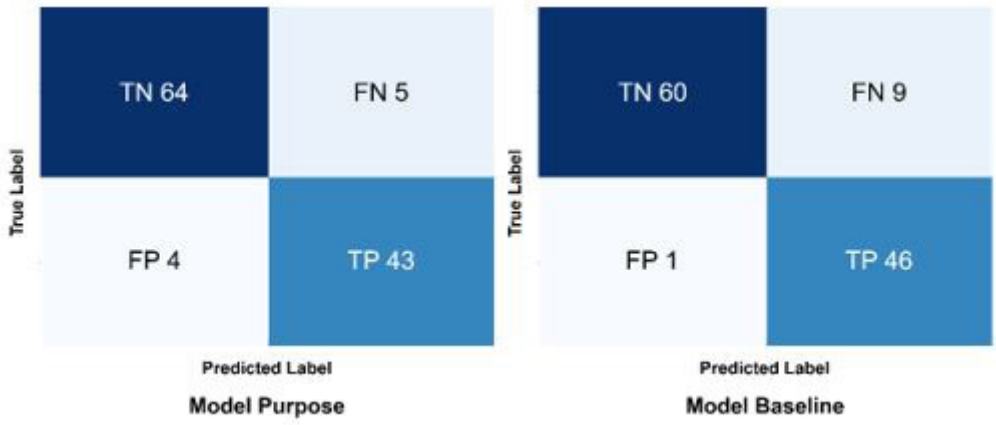

Figure 4 Model Prediction Based on Confusion Matrix

IV. CONCLUSIONS

The research succeeds in developing a new prediction model based on the ANN algorithm, especially its application to the NIDDK dataset. This prediction model is a more general prediction model than other popular prediction models by using relevant parameters for the purpose of diagnostic analysis of individuals with DM cases without focusing on a specific group. The proposed model is an improvement model from the baseline model that implements the configuration of hyperparameter cross-validation and L1 regularization. The architecture of the ANN prediction model is built using three hidden layers with a neuronal ratio of 14:20:26 with the activation function of ReLU and Sigmoid. The final performance of the prediction model obtains an accuracy value of 0.947, precision of 0.895, recall of 0.914, and model loss of 0.215. The performance results of the model show efficiency in predicting DM cases against actual cases with high accuracy.

Efforts to improve model performance can be further carried out in future research by exploring the formation of a more efficient ANN model architecture and searching for hyperparameter configurations or adding other hyperparameters such as learning rate, batch size, and number of epochs. In addition, the determination of the best hyperparameters can also be done using optimization techniques such as random search or Bayesian optimization. Then, the condition of overfitting or underfitting in a prediction model remains a looming threat in the midst of the limitations of the dataset used. Much effort is needed to handle this, one of which is by applying regularization techniques. It is a general step that can be taken to improve the condition. There are two other techniques besides L1 regularization applied that need to be considered in future research, such as the L2 regularization and dropout technique.

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REFERENCES

Al Sadi, K., & Balachandran, W. (2023). Prediction model of type 2 diabetes mellitus for Oman prediabetes patients using artificial neural network and six machine learning classifiers. *Applied Sciences*, *13*(4), 1–22. https://doi.org/10.3390/app13042344

Alifiah, N., Kurniasari, D., Amanto, & Warsono. (2023). Prediction of COVID-19 using the Artificial Neural Network (ANN) with k-fold cross-validation. *Journal of Information Systems Engineering and Business Intelligence*, *9*(1), 16–27. https://doi.org/10.20473/jisebi.9.1.16-27

Anil, A. K. P., & Singh, U. K. (2023). An optimal solution to the overfitting and underfitting problem of healthcare machine learning models. *Journal of Systems Engineering and Information Technology (JOSEIT)*, *2*(2), 77–84. https://doi.org/10.29207/joseit.v2i2.5460

Benmansour, H. (2021, June). *Predict diabetes based on diagnostic measures*. Kaggle. https://www.kaggle.com/datasets/houcembenmansour/predict-diabetes-based-on-diagnostic-measures

Chandra, J. B., & Nasien, D. (2023). Application of machine learning k-nearest neighbour algorithm to predict diabetes. *International Journal of Electrical, Energy and Power System Engineering (IJEEPSE)*, *6*(2), 134–139.

Dewi, D. D., Qisthi, N., Lestari, S. S. S., & Putri, Z. H. S. (2023). Perbandingan metode neural network dan support vector machine dalam klasifikasi diagnosa penyakit diabetes. *Cerdika: Jurnal Ilmiah Indonesia*, *3*(9), 828–839. https://doi.org/10.59141/cerdika.v3i09.662

Feng, X., Cai, Y., & Xin, R. (2023). Optimizing diabetes classification with a machine learning-based framework. *BMC Bioinformatics*, *24*, 1–20. https://doi.org/10.1186/s12859-023-05467-x

Halim, S. F. N., & Azmi, U. (2023). Analisis perbandingan klasifikasi dan penerapan teknik SMOTE dalam imbalanced data pada credit card default. *Jurnal Sains dan Seni*, *12*(2), D127–D134. https://doi.org/10.12962/j23373520.v12i2.111833

Handayani, M., Riandini, M., & Situmorang, Z. (2022). Perbandingan fungsi optimasi neural network dalam klasifikasi kelayakan calon suami. *Jurnal Informatika*, *9*(1), 78–84. https://doi.org/10.31294/inf.v9i1.12318

Izzo, A., Massimino, E., Riccardi, G., & Della Pepa, G. (2021). A narrative review on sarcopenia in type 2 diabetes mellitus: Prevalence and associated factors. *Nutrients*, *13*(1), 1–18. https://doi.org/10.3390/nu13010183

Kadhim, Z. S., Abdullah, H. S., & Ghathwan, K. I. (2023). Automatically avoiding overfitting in deep neural networks by using hyper-parameters optimization methods. *International Journal of Online and Biomedical Engineering (IJOE)*, *19*(05), 146–162. https://doi.org/10.3991/ijoe.v19i05.38153

Li, M. (2023). A practical significant technic in solving overfitting: Regularization. In *Proceedings of the 2nd International Conference on Computing Innovation and Applied Physics (CONF-CIAP 2023)* (pp. 253–258). https://doi.org/10.54254/2753-8818/5/20230433

Maulana, M. R., Abdunnur, & Syahrir, M. R. (2022). Analisis kuartil, desil dan persentil pada ukuran panjang udang loreng (Mierspenaeopsis sculptilis) di perairan Muara Ilu Kabupaten Kutai Kartanegara. *Jurnal Tropical Aquatic Sciences*, *1*(1), 10–16. https://doi.org/10.30872/tas.v1i1.467

Michelucci, U. (2018). *Applied deep learning: A case-based*

approach to understanding deep neural networks. Apress. https://doi.org/10.1007/978-1-4842-3790-8

Mustafa, H., Mohamed, C., Nabil, O., & Noura, A. (2023). Machine learning techniques for diabetes classification: A comparative study. *International Journal of Advanced Computer Science and Applications (IJACSA)*, *14*(9), 785–790. https://doi.org/10.14569/IJACSA.2023.0140982

Mustofa, F., Safriandono, A. N., Muslikh, A. R., & Setiadi, D. R. I. M. (2023). Dataset and feature analysis for diabetes mellitus classification using random forest. *Journal of Computing Theories and Applications*, *1*(1), 41–49. https://doi.org/10.33633/jcta.v1i1.9190

Naseem, A., Habib, R., Naz, T., Atif, M., Arif, M., & Allaoua Chelloug, S. (2022). Novel Internet of Things based approach toward diabetes prediction using deep learning models. *Frontiers in Public Health*, *10,* 1–11. https://doi.org/10.3389/fpubh.2022.914106

Nguyen, T. A., Ly, H. B., & Tran, V. Q. (2021). Investigation of ANN architecture for predicting load-carrying capacity of castellated steel beams. *Complexity*, *2021*(1), 1–14. https://doi.org/10.1155/2021/6697923

Nurul Anisa, D., & Jumanto. (2022). Klasifikasi penyakit diabetes menggunakan algoritma Naive Bayes. *Dinamika Informatika*, *14*(1), 33–42.

Piko, P., Werissa, N. A., Fiatal, S., Sandor, J., & Adany, R. (2021). Impact of genetic factors on the age of onset for type 2 diabetes mellitus in addition to the conventional risk factors. *Journal of Personalized Medicine*, *11*(1), 1–17. https://doi.org/10.3390/jpm11010006

Prasetyo, A. B., & Laksana, T. G. (2022). Optimasi algoritma K-Nearest Neighbors dengan teknik cross validation dengan streamlit (Studi data: Penyakit diabetes). *Journal of Applied Informatics and Computing (JAIC)*, *6*(2), 194.

Prasetyo, S. Y. (2023). Prediksi gagal jantung menggunakan artificial neural network. *Jurnal Saintekom : Sains, Teknologi, Komputer dan Manajemen*, *13*(1), 79–88. https://doi.org/10.33020/saintekom.v13i1.379

Richens, J. G., Lee, C. M., & Johri, S. (2020). Improving the accuracy of medical diagnosis with causal machine learning. *Nature Communications*, *11,* 1–9. https://doi.org/10.1038/s41467-020-17419-7

Sharma, T., & Shah, M. (2021). A comprehensive review of machine learning techniques on diabetes detection. *Visual Computing for Industry, Biomedicine, and Art*, *4*, 1–16. https://doi.org/10.1186/s42492-021-00097-7

Sihombing, P. R., Suryadiningrat, Sunarjo, D. A., & Yuda, Y. P. A. C. (2023). Identifikasi data outlier (pencilan) dan kenormalan data pada data univariat serta alternatif penyelesaiannya. *Jurnal Ekonomi dan Statistik Indonesia, 2*(3), 307–316. https://doi.org/10.11594/jesi.02.03.07

Syukron, A., Sardiarinto, Saputro, E., & Widodo, P. (2023). Penerapan metode SMOTE untuk mengatasi ketidakseimbangan kelas pada prediksi gagal jantung. *Jurnal Teknologi Informasi dan Terapan*, *10*(1), 47–50. https://doi.org/10.25047/jtit.v10i1.313

Thotad, P., Bharamagoudar, G. R., & Anami, B. S. (2022). Predictive analysis of diabetes mellitus using decision tree approach. In *2022 2nd Asian Conference on Innovation in Technology (ASIANCON)* (pp. 1–7). https://doi.org/10.1109/ASIANCON55314.2022.9909122

Vijayalakshmi, V., & Venkatachalapathy, K. (2019). Deep neural network for multi-class prediction of student performance in educational data. *International Journal of Recent Technology and Engineering (IJRTE)*, *8*(2), 5073–5081. https://doi.org/10.35940/ijrte.B2155.078219

Zaman, Z., Shohas, M. A. A. A., Bijoy, M. H., Hossain, M., & Al Sakib, S. (2022). Assessing machine learning methods for predicting diabetes among pregnant women. *International Journal of Advancement in Life Sciences Research*, *5*(1), 29–34. https://doi.org/10.31632/ijalsr.2022.v05i01.005