



Enhancing Recruitment Efficiency in the Indonesian Pharmaceutical Industry Using Backpropagation Neural Network

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Abstract

PT K-24 Indonesia is one of the foremost companies in Indonesia, with a primary focus on distributing pharmaceutical products and healthcare services. Over the last two years, PT K-24 has received more than 110,000 job applicants, offering various position vacancies. The recruitment process began with registrations, online tests, and interviews. The need for manpower has increased annually in recent years. More attention is required when selecting prospective employees who meet the selection criteria. However, PT K-24 found that the recruitment process was less efficient because the applicants did not meet the company's criteria. To overcome this problem, it is necessary to create an employee selection model for candidate selection. This study developed a recommendation using the multilayer perceptron method, namely, backpropagation. The results of this study add to the confidence of prior research that the backpropagation algorithm is effective for prediction and reliable for similar prediction tasks. This study found that using 112,397 relevant data, 23 input parameters, 1 hidden layer containing 10 neurons, ReLu activation function, and Adam solver produced better prediction, with an MSE of 0.029. Our study contributes to the methodological approach by implementing real-world problems and measuring specific criteria relevant to the selection process.

Keywords: backpropagation; deep learning; employee selection model; multi-layer perception; recruitment

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1. Introduction

PT K-24 Indonesia (K-24) distributes pharmaceutical products and healthcare services and has become one of Indonesia's biggest pharmacy companies, with 750 stores across 29 provinces and 152 cities. The number of employees is around 1000, with various positions handling and managing the company's operations. Over the last 2 years, more than 110,000 job applicants were in all positions, levels, and locations. Employee recruitment consists of three serial stages: online registration, various online tests, and interviews. The Human Resource Development (HRD) department manages the selection process through those three stages. HRD conducts a follow-up process after the second stage by interviewing the candidates to observe whether they meet the company's requirements. All selections carried out by HRD are done manually, which requires a lot of time and energy, especially in selecting the results of online registration and tests. Extant studies found that the results of the interview

selection process did not match the needs and expectations of the company, causing inefficiency in the interview stage [1] - [3].

Prior research suggested that prediction model are required to increase the efficiency rate of the employee recruitment process. The employee selection model is developed using some input parameters to select the candidates. As a result, this system can display a list of applicants who have the greatest likelihood of passing the interview process [4] - [7]. A reliable employee selection model will allow HRD staff to concentrate on shortlisted candidates, speeding up the recruitment process and increasing the likelihood of finding the right candidate. A machine learning-based prediction system is one of the methodologies that solved this issue.

Previous research developed machine learning-based prediction systems with algorithms such as Regression, Random Forest, Decision Trees, and Naïve Bayes [6], [7]. Most of these studies show the success of machine

learning models with good accuracy and relatively low error values [6]. Apart from that, recommendation systems in the education sector provide recommendations for books and courses recommendations made using the Content-Based Filtering algorithm [8], [9]. Extant studies use backpropagation to make predictions for daily activities such as shipping goods, the agricultural sector, and diagnosis of the health sector [6], [10]. The application of deep learning methods such as Artificial Neural Networks (ANN) used around 9,000 sample data to result in a model accuracy of 74% [11].

The existing literature reveals certain gaps identified from the prior studies [7]. First, IQ test data and personality scores have not been used as input parameters. These two input parameters can influence the placement test and are usually utilized to measure the candidate's cognitive abilities and suitability of the candidate with the company's culture. Second, prior studies used data from open sources, such as from Kaggle [12], [13]. Using data from open sources will make limited practical contributions because each company has different policies and work cultures. It cannot solve real-world problems as well. In addition, the limited amount of training data affects the reliability of the modeling results obtained [6]. Many studies conducted using backward propagation focus on binary targets that limit the possibilities, including [12], [14].

This study uses some input parameters and applies them to the machine-learning backpropagation method to provide shortlisted job applicant candidates. This research aims to predict the result of interview selection in K-24 based on the applicant profile and the result of the online test conducted in the initial stage using Backpropagation. Further, this research uses real-world problem data from K-24, starting from 2022 to 2024, which overlooks in prior research ([11] and [12]). The backpropagation method is the solution to this case study since the prediction accuracy [2] and [14]. Also, a prior study [12] shows that ANN provides good prediction accuracy and can learn data flexibility that is not always achieved in the Decision Tree and SVM methods. Furthermore, we extend the current studies by applying real-world data to test whether the backpropagation method can have the same accuracy results in solving real-world problems. This study also highlights that more complex and non-linear data relationships can apply the backpropagation algorithm.

2. Methods

The research methodology consists of several steps: data collection, data cleaning, determination of independent variables, data preprocessing, model building, model evaluation, and visualization of prediction results. Figure 1 shows the relevant data analysis stages.

The data preprocessing stage has three processes: data cleaning, normalization, and splitting. Data cleaning

prepares the data to be more useful in model training. The data normalization processes the data for increased model performance. Lastly, data splitting divides the dataset into training and testing subsets, allowing for robust model evaluation.

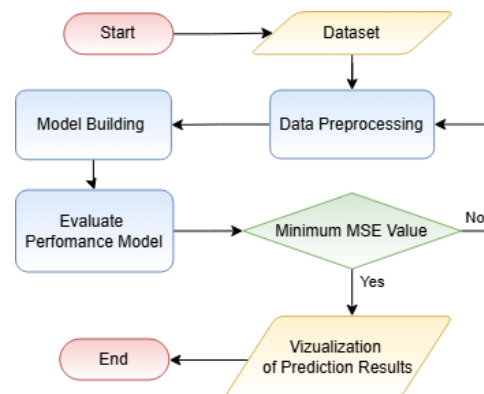


Figure 1. Data Analysis Stages

Experiments were executed by exploring the network architecture configuration of the backpropagation model. Therefore, experiments were executed using 1 to 6 hidden layers, with neurons ranging from 5 to 100 in each layer. The experiments also had other parameters and iteration sizes between 10, 20, and 100 iterations. In addition, various activation functions and solver parameters. The purpose of this experiment was to determine the best network architecture configuration.

2.1 Dataset

Our dataset was received from K-24 job applicants and test results from January 2022 to August 2024 totaling 118,908 applicants. The data used received consent from K-24 before conducting this study. K-24 allows researchers to use the data for research purposes only. The raw data consists of CSV data in the form of an applicant profile with 38 columns and 118,908 rows of data information regarding biodata, last education, and job positions applied for. Two files of online test results consisting of 7 columns of psychological test results with 433,203 rows of data. In the psychological test data, the results of each candidate's test are presented in a row, resulting in the total number of rows far exceeding the number of candidates. The second test has 10 columns of personality test results with 82,896 rows of data in four types: dominance, influence, steadiness, and compliance (DISC). After that, there are two interview result files: the HRD interview with 136,800 rows of data and the User interview results with 6,907 rows of data.

Finally, an Excel file that stores the list of accepted applicants has 3,966 candidate data. The difference in file types is not an obstacle in research because the two types of files have almost the same data structure. Next is the data preprocessing stage, with the first step being data cleaning.

2.2 Data Cleaning

The steps of data cleaning are: (1) Removing duplicate data, (2) Handling data that does not match columns, (3) Removing data columns, (4) Handling outliers, (5) Adjusting data types, (6) Handling blank values, (7) Categorizing data, and (8) Data transformation.

Each step in the cleaning stage has its purpose. The stage of removing duplicate data serves to eliminate redundancy by ensuring that each piece of data only appears once. Secondly, removing mismatched data ensures that each piece of information is in the correct column, thus improving the accuracy of the data. Thirdly, removing columns that do not contribute to the analysis increases the focus on relevant columns. Fourth, addressing outliers by removing or replacing data values appropriately can improve the data set and increase the reliability of the analysis. Data type adjustment determines a consistent data type format for each column. Sixth, handle missing values to maintain the integrity of the data set by filling the missing values with a constant such as 0. This cleaning technique is helpful to ensure the accuracy of the analysis results and provide more informed conclusions.

Categorizing data that has the same meaning aims to achieve consistency more effectively. Data categorization can be done using three options: first, changing the data value by replacing the value with another value according to the meaning of the column. The second alternative is using rules or creating certain functions designed according to column specifications. Finally, a Natural Language Processing (NLP) based categorization dictionary such as Word2Vec can facilitate a smoother analysis, which can help to categorize the data.

Table 1. List of Profile Data Columns

No	Column Name	Value Column
1.	candidate id	ID of each candidate
2.	age	the age of each candidate
3.	gender	female or male
4.	marital status	married, unmarried, widow, or widower
5.	child category	single, eldest, middle, or youngest
6.	last education	SMA, SMK, D1, D2, D3, D4, S1, S2, or Profession
7.	last education major code	code from the candidate's last educational major
8.	school category	high school, vocational school, university, polytechnic, polyclinic, high school, or academy
	Grade Point Average or Final Grade	GPA is an academic grade, so for applicants who graduated from S1, the GPA value will be between 0-4, while applicants who graduated from SMK are worth 0-100

The last cleaning step is data transformation, which restructures the data frame for storing applicant data. So that the applicant data has one row with different test result columns to facilitate data analysis and interpretation. Therefore, the data is ready to continue to the next stage. The final applicant profile data is obtained with nine columns, as discussed in Table 1.

The online test result data consists of 7 columns of psychological test results and 10 columns of personality test results. The psychological test attributes include General Ability Test, Speed and Accuracy Test 1, Speed and Accuracy Test 2, Pharmacy Test A, Pharmacy Test B, Finance - Journal, and Finance, with scores categorized into very low, below average, average, and above average. Attributes for personality test data are Most Dominance, Most Influence, Most Steadiness, Most Compliance, Most Neutral, Least Dominance, Least Influence, Least Steadiness, Least Compliance, and Least Neutral with a value range from 0 to 21.

HRD interview data consists of HRD Decisions and 10 assessment criteria namely: Enthusiasm, Innovation, Integrity, Communication Skills, Caring, Appearance, Leadership Potential, Professionalism, and Teamwork. Each criterion is evaluated using a numerical scale ranging from 1 to 5. In addition, the User interview results include a column of decision results from the user, and the last is a list of accepted candidates. This list of accepted candidates contains the candidate ID, joining date, and candidate type, which indicates the type of job section (at the Outlet or in the FSOR section). All features in all data frames are used as input features (independent variables) in the prediction model.

As shown in Table 2, the unclean data was not included in the prediction calculation. The psychological test and HR interview data are unclean because one applicant has several rows of data with different tests. During the data transformation, these data are merged, resulting in a higher percentage of gross data with 78% unclean psychological test and 89% unclean interview data, respectively. Hence, each applicant consisted of one row of data, showing each test result in a single column.

Table 2. Total Before and After Cleaning Data

No	Data Files	Before	After	Percentage of Gross Data
1.	Profile	118,908	117,932	1%
2.	Psychological Test	433,203	96,183	78%
3.	Personality Test	82,896	50,230	39%
4.	HR Interview	136,800	15,017	89%
5.	User Interview	6,907	6,907	0%
6.	Accepted Candidates	3,966	3,966	0%

After the data was cleaned, all the data sets were merged into one comprehensive data frame. A total of 121,907 merged data were obtained. However, many applicants do not have complete data, such as accepted applicants who do not have data on online test results or interview results. Applicants with incomplete data will be excluded, resulting in 112,397 as the final dataset. The dataset consists of three categories at the HR interview stage: failed (94.7%), passed (3.7%), and considered (1.6%).

2.3 Data Normalization

Data normalization was implemented after the data cleaning and merging process. It aims to standardize data with a large and varied range of values. Therefore, it is important to ensure that data comparisons are within the range and that the model can study the data more effectively and efficiently.

In this study, the normalization used is the min-max method, which aims to change the values in the data set to a consistent range between 0 to 1 [15]. Performing data normalization at the preprocessing stage with data scaling can increase accuracy even by more than 25%, and the lowest mean square error value [15] - [17]. The normalization of the min-max method can be formulated as Formula 1.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

X is the actual value of the dataset; (X_{min}) is the minimum value of the dataset; (X_{max}) is the maximum value of the dataset; and (X') the normalized value.

2.4 Split Data

The next step in the experimental process is to divide the dataset into training and testing subsets. This division is a fundamental stage in developing machine learning models, as it helps to address the risks of overfitting, where a model memorizes training data too closely, and underfitting, where it fails to capture meaningful structures in the data.

The proportion between training and testing datasets has an important impact on the overall accuracy and error rate of the model [18]. If the portion of training data is too small, the model may not have sufficient information to learn effectively. Conversely, if the portion of testing data is too small, the evaluation may not provide a reliable measure of the model's ability to generalize. Therefore, choosing an appropriate ratio is necessary to achieve a balance between learning capacity and evaluation reliability.

The `train_test_split` function was applied, and the data separation was randomized using the `random_state` parameters. The percentage of training data is 80%, while the rest is for testing data (equal to 20%).

2.5 Model

The model creation stage uses the forward propagation machine learning technique (Feed Forward Neural Network / FNN). This model-building process will use model architecture consisting of input layers, hidden layers, and output layers. In this research, FNN is used with 23 input parameters, 1 hidden layer containing 10 neurons, ReLu activation function

The specifications of the three layers in the FNN model have their different purposes. The input layer aims to receive raw data as independent variables, which will later be processed in the hidden layer. The hidden layer aims to process information from the input layer by

applying weights and adjusting weight changes when performing backward propagation [19]. The output layer, in the form of model prediction results, is categorized into 3 labels, namely, passed, considered, and not passed.

The Backpropagation algorithm is a continuation of learning from FNN, which uses many hidden layers so that it is faster to learn because the model learns from errors [10]. Adjusting the weights on the model will use backward propagation by calculating the errors that occur. This process will be carried out repeatedly until it gets a small or stable error value [19]. The backpropagation algorithm can make learning more efficient because the model can update network weights based on the number of errors occurring [14]. The design of the prediction model is accomplished using a library that is easy to implement using complex data [20].

Modeling will use the scikit-learn library, which is one of the libraries often used to solve problems related to complex regression [20]. The scikit-learn library consists of several adjustments to various important parameters for the hidden layer, including the number of hidden layers, learning rate, activation function, and solver. The learning rate serves to determine the amount of weight change for each model update [20]. The learning rate will affect the results and speed of the model training process. It is known that the large learning rate can affect the accuracy of the prediction results [13]. In addition, a learning rate that is too small will make the model training slow, while if it is too large, the model training will cause the model to become unstable [21].

The activation function parameters build a prediction model that models non-linear relationships with diverse variables. By using these parameters, the model can learn more complex data patterns. The activation function is used in the hidden layer. There are three kinds of functions, namely: logistic sigmoid, tanh, and Relu.

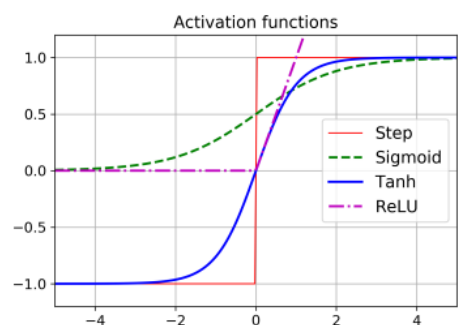


Figure 2. Various types of function activation graphs

Figure 2 shows an image of each activation function. The sigmoid logistic function will produce a binary value output (0,1) that is more appropriate for binary/binary probabilistic classification. Generally, backward propagation models will use sigmoid activation functions [13] and [21].

The tanh function will produce outputs in the range $(-1,1)$, showing that the outputs will be more dispersed than the logistic function. The tanh function is often used to distinguish between negative and positive values. Lastly, the activation function used in this research is the ReLu function as given in Formula 2.

$$\text{ReLu} = \max(0, x) \quad (2)$$

The Relu function in equation 2 will only produce positive outputs; if there is a negative value, the function will return to a value of 0. Additionally, the ReLu activation function is often widely used and provides great model-accuracy results [22].

The solver is responsible for optimizing the model by determining the bias and weights of the updated network to minimize the loss function. Applying solver parameters to the model can affect the speed and stability of the data training process [20]. There are three types of solvers, namely LBFGS (Limited-memory Broyden Fletcher Goldfarb Shanno), SDG (Stochastic Gradient Descent), and Adam (Adaptive Moment Estimation). One of the parameter optimizations (solver) on large-scale data can accelerate convergence in the cluster [23]. The solver used in this research is the Adam solver.

The selection of activation functions and solvers are the two most important parameters because both have a direct influence on model learning. The three activation functions and solvers will be used and compared in this study. This aims to determine the most optimal activation functions and solvers to improve prediction accuracy in the employee recruitment process.

2.6 Model Evaluation

In order to assess the performance of a predictive model, it is necessary to apply specific evaluation metrics that provide an objective measure of accuracy and error. For the Multi-Layer Perceptron (MLP) model, model can be evaluated by measuring metrics of error magnitude such as MSE, RMSE, and R-squared [19].

Several studies and this research use the calculation of model evaluation with MSE [19], [24]. MSE measures the performance model with the average square metric of the difference between the predicted value and the actual value [25].

$$\text{MSE} = \sqrt{\frac{1}{T} \sum_{t=1}^T (x_t - \hat{X}_t)^2} \quad (3)$$

In the MSE formula in Formula 3, the value (x) is the average value of the time series, (T) is the number of elements, the value (x_t) is the time series element, the value $(\hat{X}_t)$ is the predicted value [21].

2.7 Visualizations

Data visualization is an important step to make prediction results easier to interpret. In this research, the visualization was developed using the Streamlit

framework to provide an interactive display. The system presents prediction results by listing the top 10 applicants with the highest scores first. Each applicant's profile can be expanded to show detailed biodata and test results, while navigation buttons allow users to move to the next or previous list of applicants. This feature ensures that all applicants can be reviewed efficiently and in an organized manner.

In addition to ranking, the visualization shows the total number of applicants along with a breakdown of those categorized as high or medium potential. To support more focused analysis, a filtering feature is provided. HRD staff can filter applicants by type, responsible HRD, job position, or placement preference. These functions make the visualization not only informative but also practical for assisting HRD in the recruitment process.

3. Results and Discussions

The experiments of the model are presented, focusing on the impact of various parameters and network architecture on the performance of the prediction model. Experiments are conducted to identify the optimal configuration that produces the highest accuracy and lowest error rate, which aims to improve the quality and efficiency of the K-24 recruitment process.

3.1 Results

Modeling is split into two levels of models shown in Figure 3. The first model is based on profile data and online test results. The dataset was categorized into three categories: 0 for failed candidates, 0.5 for HR consideration (including backup candidates), and 1 for passed candidates. The initial configuration in this research applies the ReLU activation function, which is known to be effective in handling vanishing gradient problems and uses the Adam solver for its ability to adaptively adjust the learning rate. The evaluation was conducted using randomly chosen test data (20%) derived from historical data from the recruitment process for about 2 years, so this study focused on the model's performance against the test data.



Figure 3. Research Model Stages

Table 3. Details of Configuration for Model Training

No	Configuration Parameter	Parameter Description
1.	Ratio data train: data model	80:20
2.	Number of hidden layers	1
3.	Number of neurons in the hidden layer	10
4.	Maximum number of Iteration	10
5.	Alpa	0.001
6.	Activation function	Relu
7.	Solver	Adam

The first level experiment aims to see the effect of the independent variables using the training model configuration, as shown in Table 3. Experiments using features such as profile (GPA, child category, major code, and position applied), psychology test (except the 'validation test'), and all personality test results, as mentioned in the earlier section. The experiments conducted included trials using the original personality test parameter values. The second experiment was conducted using converted personality test scores using the difference between the highest and lowest scores, as defined in Formula 4.

$$\text{Difference} = \text{Most} - \text{Least} \quad (4)$$

The result of the difference calculation from this personality test will be stored in a new column variable,

and later, an influence analysis will be carried out using the original test results (highest and lowest) with the difference calculation value. This experiment was conducted with the level 1 target model several times, using the features described in 2.2 Data Cleaning as input variables (variable independent). This experiment will use MSE evaluation to determine each feature's predicted match value. So that the output value generated by the model is a continuous numerical value, which aims to sort the highest prediction results (ranking) based on the MSE value close to 1 (passed). The features were implemented in the model training process to obtain the best performance with the MSE results as shown in Figure 4.

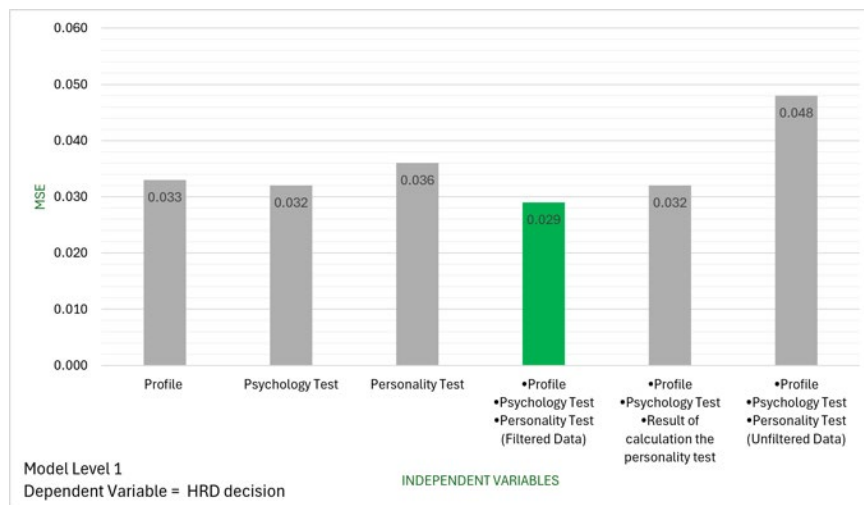


Figure 4. Impact of Independent Variables Model Level 1 on MSE

The results of the experiments in Figure 4 show that the Psycho test parameter has a large effect on the model. In addition, data filtering also has an impact on the results of the prediction model. Also, it shows that using the original DISC personality test scores results in better prediction values.

The next stage in this research is to conduct experiments to find the most suitable artificial neural network architecture and optimize the model parameters. Experimental results related to network architecture can be seen in Figure 3, while experimental results related to model parameters are presented in visual form in Figure 5.

Table 4 shows that an experiment with the specifications shown in Figure 4 is sufficient with a small network, namely with 1 hidden layer consisting of 5 neurons and 10 iterations.

The graph in Figure 5 shows that using the Relu activation function and Adam's solver gives better results. Therefore, the final results of the level 1 model using the independent variables of profile data, the second data of online test results using 1 hidden layer, 10 neuron points, 10 iterations, alpha 0.001, activation

function Relu and Solver Adam can provide high accuracy with a scaled error (MSE) of 0.029.

Table 4. Analysis of the effect of the size of the hidden layer network and the number of iterations

No	Hidden layer	Neuron Points	Iteration	MSE
1.	6	100,80,60,40,20,10	100	0.029
2.	1	100	100	0.029
3.	1	100	10	0.029
4.	1	50	10	0.029
5.	1	10	10	0.029
6.	1	5	10	0.030
7.	1	5	20	0.030

The final decision regarding the applicant's eligibility will be determined based on the prediction results of the backpropagation model. Applicants will be categorized into three groups: "not passed" (for predicted values below 0.1), 'considered' (for predicted values between 0.1 and 0.5), and 'passed' (for predicted values above or equal to 0.5). By categorizing continuous values into three categories, it is possible to see the prediction results of each category and make it easier for users (HRD) to see an overview of each candidate's potential without having to look at the continuous numbers.

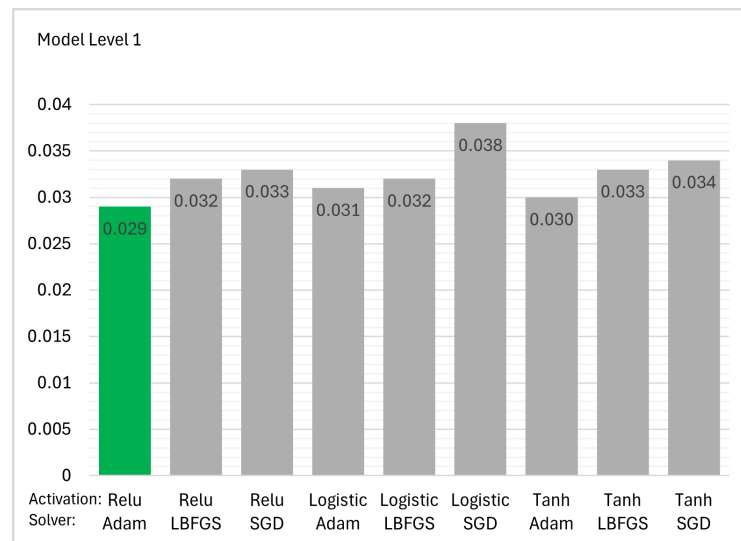


Figure 5. Impact of Activation Function & Solver on MSE

The prediction accuracy validation test was conducted using the report classification metric. Figure 6 proves an accuracy of 87%, which means that the prediction model successfully detects unsuccessful applicant data that will not appear as recommendations.

Level 2 experiments were conducted using the network model specifications in Table 4 but using the target parameter (output layer) in the form of user interview decision results. HRD interview result criteria were added to the input layer neurons. The purpose of this

level 2 model is to predict potential applicants who will pass the user interview.

	Precision	Recall	F1-Score	Support
Considered	0.11	0.81	0.19	379
Passed	0.54	0.03	0.05	831
Not Passed	0.99	0.91	0.95	21270
Accuracy			0.87	22480
Macro Avg	0.54	0.58	0.39	22480
Weighted Avg	0.96	0.87	0.90	22480

Figure 6. Level 1 Report on Model Classification

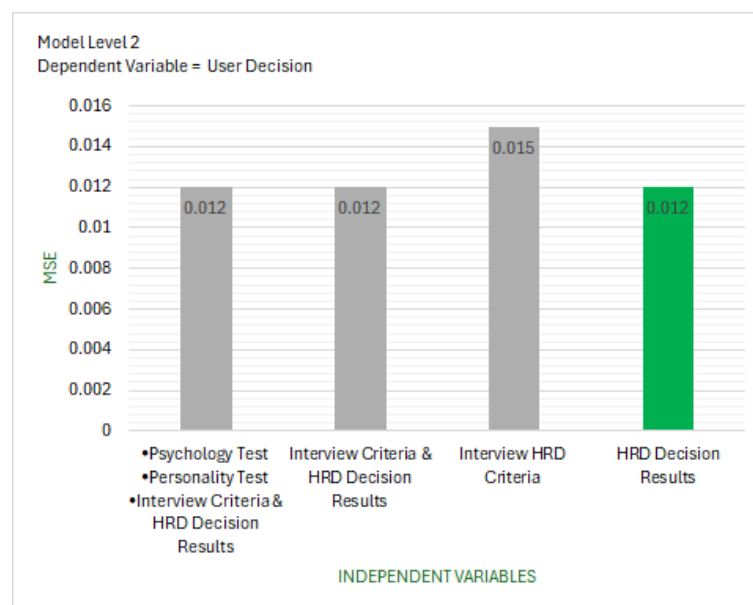


Figure 7. Impact of Independent Variables Model Level 2 on MSE

Figure 7 shows that by using only one input parameter in the form of column 'HRD decision result', the model has been able to predict the user's interview decision with a mean square error (MSE) of 0.012 and an accuracy rate of 97% in Figure 8.

The final results of the two levels of the model are visualized by displaying the test data that has been sorted based on the highest prediction results, as shown in Figure 9. This visualization aims to make HRD the user of the prediction model see the Top 10 list of

applicant names with the highest prediction results and follow up the recruitment process to the interview stage.

Figure 9 displays a potential column that shows the applicant's acceptance potential with categories of high potential (green), medium potential (yellow), and low potential (red). In addition, in Figure 10, the interface also displays detailed information on each applicant, which is separated into different tab pages in the form of applicant profiles and online test results.

	Precision	Recall	F1-Score	Support
Considered	0.04	0.59	0.08	27
Passed	0.58	0.85	0.69	561
Not Passed	1.00	0.97	0.99	21892
Accuracy			0.97	22480
Macro Avg	0.54	0.81	0.58	22480
Weighted Avg	0.99	0.97	0.98	22480

Figure 8. Level 2 Report Model Classification

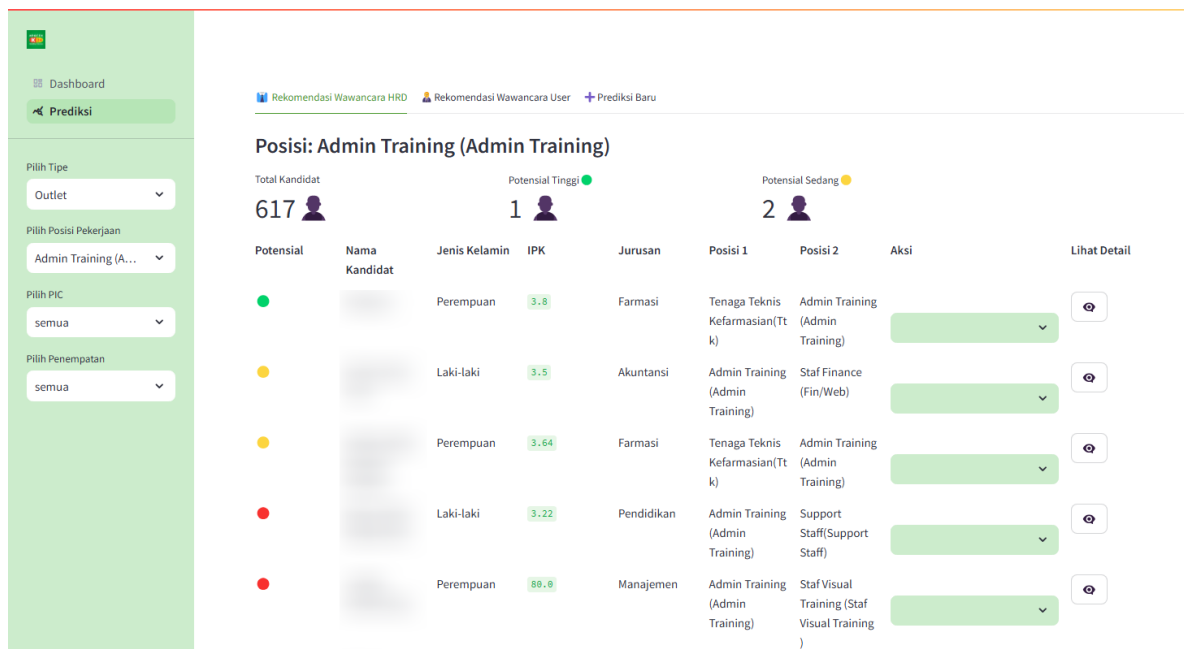


Figure 9. Prediction Results Interface

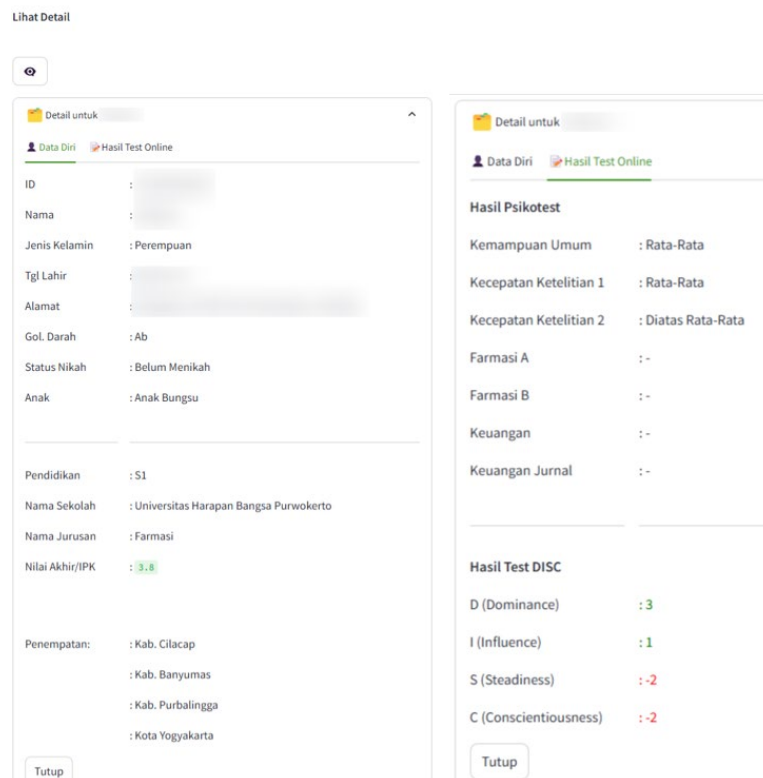


Figure 10. Applicant Details Information Interface

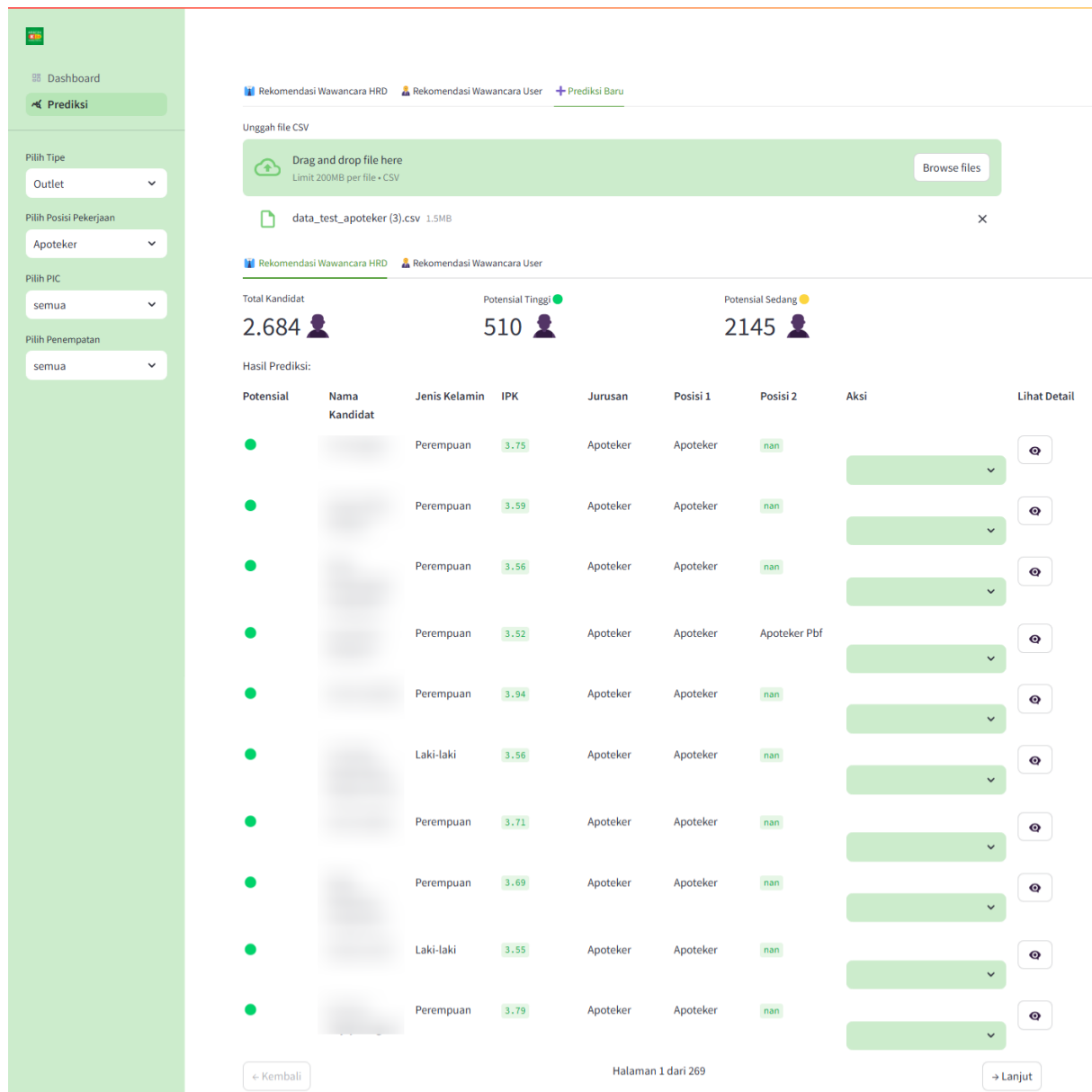


Figure 11. Prediction Interface Using the New Data

In addition to displaying test data, there is also a tab that functions to make predictions by uploading new data in the form of CSV files in Figure 11. The results of predicting new data are displayed with the same visualization in Figure 9. There is an "Action" column that aims to provide information on the continuation of the applicant's process with options, continuing the interview, being considered, and rejecting.

3.2 Discussions

This study found that through some steps and experiments, the Backpropagation method can predict K-24 applicants with a high accuracy rate (model 1: 87% and model 2: 97%). This accuracy ensures that the prediction system can identify candidates that match the k-24 criteria. By using this prediction system, K-24 can increase the speed of the employee recruitment selection process, reduce the time spent on manual screening, and improve the quality of recruitment. So

that HR can prioritize and focus on candidates capable of passing the interview process. The amount of MSE obtained in this study (model 1: 0.029 and model 2: 0.012) is lower than the results of previous research [12], which received an MSE of 0.45 with the prediction and the application of a similar methodology. In addition, the experiment result explains that using the most influential input parameter or independent variable can already give a good prediction, compared to using various and many parameters.

The original data from the personal test results described the variation between variables better than the data calculated from the difference between the 'most' and 'least' values. The difference between the two experiments is 0.018, which shows that the backpropagation method can improve the accuracy of the model just by using the original data that is more representative of the model.

The results of hyperparameter experiments to achieve the best parameters showed that the number of hidden layers and the size of neurons did not provide significant prediction improvement results. The same thing in the results of this study with previous research is that a network that is too small can also affect the error rate [24]. This study supports prior studies [23] which demonstrate that using Adam as the solver in the Backpropagation model can accelerate the training process. Additionally, research [22] that combines the ReLu activation function and Adam solver achieve the highest accuracy by obtaining the smallest MSE value.

The existence of this prediction model provides recommendations for high-potential candidates, thus helping HRD to focus more on those candidates to continue the interview process. Although this prediction model has not been implemented directly by PT K-24, this model has good potential as a supporting tool in the candidate selection process.

4. Conclusions

Based on the results of this study, the model Backpropagation shows a high level of accuracy in predicting potential recruitment applicants who will pass the interview stage. The level 1 model provides an accuracy of 87% with a target with the output of potentially passing the HRD interview with an evaluation of the Mean Squared Error of 0.029. Then, the level 2 model with 97% accuracy with the output target potentially passing the User interview with MSE 0.012. In addition, the prediction model constructed has generated accurate results by using a small network structure (1 hidden layer consisting of 10 neurons and 10 iteration) and selecting the appropriate parameter combination (activation function is ReLu and the solver is Adam). This research offers an efficient and accurate recruitment and selection process, maximizing the operational process. Hence, it can provide a rigorous machine-learning application to enhance the recruitment and selection process. Using a high-accuracy prediction model can be a useful tool for HRD PT. K-24. Especially by a decision-making tool to continue prospective candidates to the interview stage more efficiently and by the expected criteria. So that HRD can prioritize and focus on more potential candidates.

This study has some limitations that can be addressed in future research. Some suggestions can apply to further research, such as developing prediction models that have been made by evaluating the most important independent variables or comparing the Backpropagation method with other machine learning methods.

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