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Stunting Disease Classification Using Multi-Layer Perceptron Algorithm with GridSearchCV

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Abstract: Stunting is a growth and development disorder caused by malnutrition characterized by a child's height less than the standard deviation set by WHO. In 2022, stunting cases in Indonesia are considered a high prevalence rate, reaching 21.6%. There are several factors that can cause stunting in children, namely maternal and antenatal care factors, home environment factors, breastfeeding practices, and feeding factors during toddlerhood. There are several impacts that occur when children are stunted, namely increased risk of child mortality, susceptibility to illness, impaired brain development, physical disorders and metabolic disorders. Currently, deep learning has been widely used for disease classification and prediction, one of the deep learning methods is Multi-Layer Perceptron (MLP). The purpose of this research is to classify stunting disease using a deep learning method, namely MLP. The dataset used consists of 8 attributes, namely gender, age, birth weight, birth length, body weight, body length, breastfeeding and stunting with a total of 10,000 records. The encoding process is carried out to convert categorical data into numeric attributes of gender, breastfeeding, and stunting. This research produces a higher accuracy value than previous research which used the C4.5 algorithm with an accuracy of 61.82%, whereas in this study using MLP which was integrated with the GridSearchCV hyperparameter it obtained an accuracy of 82.37%. This proves that the MLP method is successful in classifying stunting compared to previous research algorithms.

Keywords: Classification; Deep Learning; Disease; GridSearchCV; Multi-Layer Perceptron; Stunting

INTRODUCTION

Stunting is a crisis problem in the field of health and welfare that is of concern in various countries, including Indonesia.In 2022, the prevalence of stunting in Indonesia is considered high with a figure of 21.6% based on the results of the Indonesian Nutrition Status survey (Kemenkes RI, 2023).Even according to the World Health Organization (WHO), in 2022 there were 148.1 million children under the age of 5 years experiencing stunting (WHO, 2023).Stunting is a disorder of child growth and development caused by chronic malnutrition characterized by the condition of infants who have a height less than 2 times the average standard deviation of growth set by WHO (Rahmi et al., 2022). Stunting is mostly experienced by children under 5 years old, where as much as 70% of stunting occurs in the age range of 0 - 23 months (Pohan et al., 2021). The impact that can arise due to lack of nutrition in children can increase the risk of child mortality, sufferers are susceptible to illness, disruption of brain development, physical disorders and metabolic disorders (Astarani et al., 2020) (Wahyudin et al., 2023).

*Christian Sri Kusuma Aditya

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Factors associated with and at risk for stunting are caused by the status of nutritional intake consumed during infancy. Inadequate nutritional intake can affect physical growth in children.There are several factors that cause children to experience stunting, namely (1) maternal and antenatal care factors, (2) home environment factors, (3) breastfeeding practice factors, and (4) feeding factors when under five (Mediani et al., 2023).

Along with current technological developments, machine learning and deep learning methods have been widely used to provide solutions to problems that occur, including problems in the medical field (Purbolaksono et al., 2021). Deep Learning is a subfield of machine learning that focuses on the use of artificial neural networks. Artificial neural networks are a widely used artificial intelligence method because they have good performance, especially in transforming data so that data can be processed more easily (Firmansyah & Hayadi, 2022). Artificial neural networks have advantages over other conventional classification methods, which are more reliable against noise in the data (Wibawa & Maysanjaya, 2018). In addition, artificial neural networks also have the ability to produce good predictions to solve a problem despite using a limited number of samples (Panca Saputra & Panca, 2020). Artificial neural networks have been widely applied in various fields for pattern recognition, pattern classification and pattern prediction (Selwal & Raoof, 2020).

There are several studies conducted to predict various diseases classification. One of the methods in deep learning that can be used for classification is the Multi-Layer Perceptron (MLP). There is research conducted to classify breast cancer using MLP with an accuracy of 97.7% (Kusuma, et al., 2022). MLP has the main advantages of its high classification speed and efficient algorithms that operate quickly and the ability to extract complex patterns for relationships that may be difficult to understand by conventional classification methods (Wang et al., 2019). In addition, there is also research conducted to predict heart disease resulting in an accuracy of 81.19% and 90.57% (Kurniawan & Silvanie, 2021). Training was carried out in 300 epochs and 10 batches. The results are in the form of weights for each neuron in the ANN. The model accuracy metric value was obtained at 81.19% with a sensitivity value of 99.39% and a specificity value of 94.93%. On the other hand, research on identifying stunting in children has been carried out using the c4.5 algorithm, the evaluation of the model using the Confusion matrix resulted in the highest accuracy of 61.82% and AUC of 0.584 (Yunus et al., 2023).

Therefore, this study aims to improve the performance of classification modeling results from previous research by proposing the use of the Multi-Layer Perceptron (MLP) method to identify stunting in children. The search for the optimal combination of parameter values is carried out to improve the model performance of the MLP, the use of GridSearchCV involves a combination of hyperparameters and evaluation of model performance using cross-validation by exploring the hyperparameter space. (Ahmad et al., 2021).

LITERATURE REVIEW

MLP, also known as Multi-Layer Feedforward Neural Network, is a deep learning algorithm that excels in determining weight values when compared to other methods (Riyanto, 2018). MLP has 3 layers of processing, namely input layer, hidden layer, and output layer (Nurrokhman, 2023). MLP capabilities such as being able to adapt to input data and being able to predict relationships between classes and object attributes, and overcome model problems quite well. These capabilities make MLP popular in classification cases (Jiang & Xu, 2022). MLP is also one of the main deep learning algorithms because it has great potential in the development of technology in the field of medicine (Sharma et al., 2022). Therefore, this research is focused on the use of classification methods with MLP.

Previous research has conducted research related to the issues raised and used the MLP method for classification and prediction of various diseases such as research conducted for the classification of thyroid disease resulting in an accuracy of 99.2% using 7 attributes and 100% using 11 attributes (Selwal & Raoof, 2020). Then there is research using the same method for chronic kidney disease classification problems resulting in an accuracy value of 92.5% (Vashisth et al., 2020). Other research conducted to predict alzheimer's disease using the same method obtained an accuracy of 94% (Jyotiyana & Kesswani, 2020). Other research was also conducted with the problem of heart disease classification with an accuracy of 90.57% (Nurrokhman, 2023). There is also research with breast cancer cases using the MLP

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method and each prediction has achieved an accuracy value of 91.19% and 98.9% (Desai & Shah, 2021) (Yellamma & Journal, 2020).Based on the research that has been done, it is proven that the use of the MLP method in disease classification problems has succeeded in getting a high level of accuracy in predicting and classifying diseases.

METHOD

This research will classify stunting disease using the MLP algorithm method. MLP is a type of artificial neural network consisting of several neural layers that can be used in the classification, regression, and prediction processes using validation techniques to train and test pre-processed data to get the best results (Azmat et al., 2022). The flow of research stages is depicted in Fig. 1 with a mutually involved process, starting from data preprocessing which is done by taking the stunting dataset, then selecting features, deleting empty data and duplicate data, to separating data into training data and test data. The following are some of the stages carried out in data processing for the classification of stunting disease.

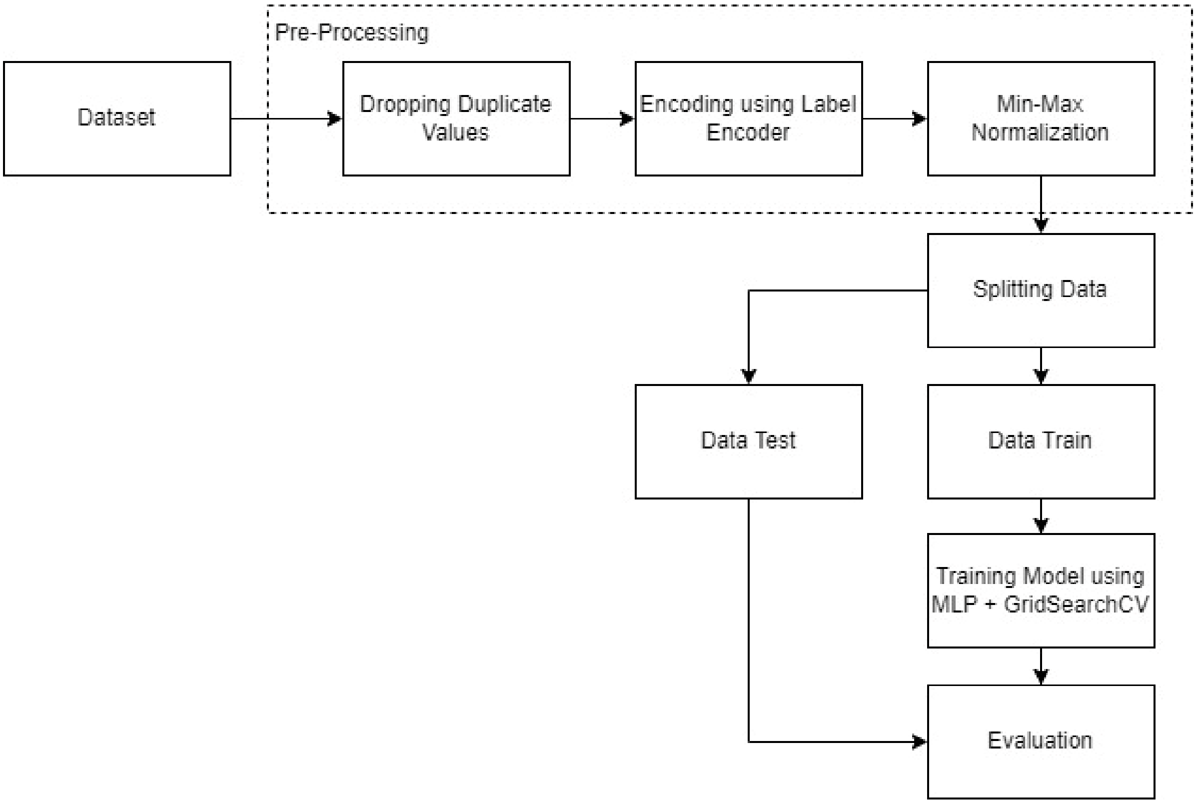

Fig. 1 Research Flow

Dataset

Dataset is a collection of raw data in the form of a table that contains a number of information related to data that can be processed and analyzed as shown in Table 1. The dataset used in this research is public tabular data which is divided into two data, namely test data and training data. The dataset consists of 8 attributes and 10,000 records.

Table 1. Dataset Information

*Christian Sri Kusuma Aditya

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Atribut	Description
Gender	Contains categorical gender data that has the values 'Male' and 'Female'
Age	Contains numeric data that shows the age of toddlers
Birth Weight	Contains numerical data that shows the weight of toddlers at birth
Birth Length	Contains numerical data that shows the length of a toddler's body at birth
Body Weight	Contains numerical data indicating the weight of a toddler at that age
Body Length	Contains numerical data indicating the length of a toddler at that age
Breastfeeding	Contains categorical values of breastfeeding toddler status
Stunting	Contains the categorical value of the status of stunting toddlers

Duplicate Data

Duplicate data is an entry in the data that appears more than once in the same data. Problems with duplicate data can occur such as inconsistency, reduced data quality, and data integrity (Venkateswara Reddy & Damodaram, 2022). Therefore, removal of duplicate data is necessary so as not to interfere with the analysis and eliminate bias in the training model. After the removal of duplicate data, the total data became 7,573 records.

Encoding

Encoding is one of the data processing techniques in machine learning and data mining. Encoding is done by converting categorical data into numerical data that can be processed by machine learning algorithms. The encoding process is carried out on gender, breastfeeding and stunting attributes which have categorical data types.

Splitting Data

The data is separated into two main parts, namely training data and test data. Training data is data that is available based on the facts that occur, while test data is data that is labeled and used in calculations according to the equation of the accuracy calculation method of the classification performed on the model (Anggreani et al., 2018). In this study, data splitting was carried out into 80% training data and 20% test data.

Normalization

Normalization of data is the process of changing the scale or range of data so that all variables are balanced when processed in the model. The need for data normalization is to reduce potential process errors by converting actual data into values with an interval range of 0-1 (Ni Kadek Ary Indah Suryani et al., 2022).

As can be seen in Table 2, there are several attributes that have a continuous value in the range 0 - 1 which will be normalized, including Age, Birth Weight, Birth Length, Body Weight and Body Length. Meanwhile, the attribute values for gender, breastfeeding and stunting are nominal values between 0 or 1.

Table 2. Normalization Value

*Christian Sri Kusuma Aditya

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Gender	Age	Birth Weight	Birth Length	Body Weight	Body Length	Breastfeedin g	Stunting
1	0.21	0.81	0.50	0.55	0.50	0	0
0	0.14	0.90	0.50	0.73	0.32	0	1
0	0.11	0.27	1.00	0.46	0.36	0	1
1	0.04	0.63	0.50	0.63	0.36	0	1
1	0.16	0.90	1.00	0.46	0.53	0	1

Hyperparameter Tuning GridSeacrh CV

There are several aspects that affect the results obtained by MLP such as data parameters, MLP parameters, and parameters in the model training process (Ngoc et al., 2021). Hyperparameters are external parameters that cannot be learned by the model during the training process, and tuning focuses on finding the combination of hyperparameter values that produces the best model performance. This tuning process involves experimenting with various hyperparameter values, using the GridSearchCV method. GridSearchCV is a method used to identify the optimal parameters of a classifier so that the model can accurately predict some unlabeled data [Siji George & Sumathi, 2020].

It's important to recognize that determining the optimal hyperparameter values in advance is challenging. Ideally, it would explore all potential values to find the best ones. However, manual exploration is time-consuming and resource-intensive. To streamline this process, GridSearchCV is employed to automate the hyperparameter tuning, allowing for a systematic search across various values to identify the optimal configuration.

Training Model using MLP

In machine learning, training data will be used to train a model that functions so that the model can identify patterns contained in the data and is used to classify whether a child experiences stunting symptoms or not based on the variables that have been obtained.

Multi Layer Perceptron is also known as MLP. It is fully connected dense layers, which transform any input dimension to the desired dimension. A MLP is a neural network that has multiple layers (Kwon et al., 2017). A MLP consists of an input layer where each input corresponds to a single neuron, an output layer with neurons representing the outputs, and an arbitrary number of hidden layers. Each hidden layer can contain varying numbers of nodes. The representation of MLP learning is as shown in Fig 2.

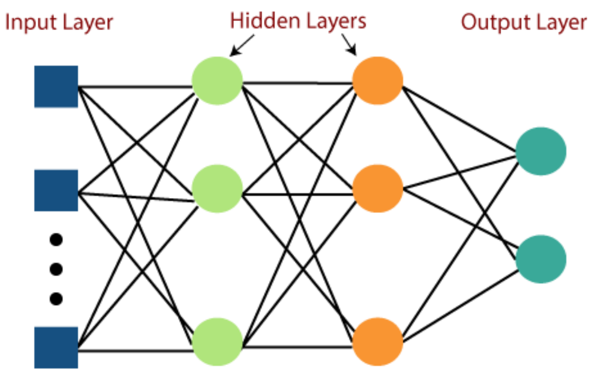

Fig. 2 Multi-layer Perceptron Architecture

In a multi-layer perceptron (MLP), equation 1, data moves forward from the input to the output layer, similiar to a feedforward network. The neurons within the MLP undergo training using the

*Christian Sri Kusuma Aditya

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backpropagation learning algorithm. MLPs are specifically crafted to approximate any continuous function, enabling them to address problems that lack linear separability. The layers of an MLP consists of several fully connected layers because each unit in a layer is connected to all the units in the previous layer (Azmat et al., 2022).

$$y = f(\sum_{i=1}^{m} w_i * x_i) + b \quad (1)$$

Explanation:
x_i = input to the MLP
w_i = weights that connect each neuron in the previous layer to neurons in the next layer
b = bias added to each neuron in the next layer
f = activation function used by each neuron
y = output of the MLP

Evaluation

The final process after the data has been trained is to evaluate the performance of the model using the previously separated test data. A common method is to calculate the accuracy value. The accuracy obtained will determine the extent to which the model predicts correctly. Another test method is to calculate the precision and recall values. The precision value will measure the positive class in the model when the model predicts and recall to measure the model in the process of identifying all instances of the positive class. Then there are also F1-Score and Confusion Matrix methods. F1-Score is the average harmonic value of the precision and recall values. Meanwhile, Confusion Matrix is a metric that provides a mixture of predicted and actual classes (Markoulidakis et al., 2021). The results of the evaluation will show the extent to which the model is able to classify stunting symptoms well and whether or not the model needs to be further improved and enhanced.

RESULT

This research provides results in the form of accuracy levels obtained from tests that have been carried out with the aim of testing the accuracy and performance of the MLP method by applying GridSearchCV hyperparameter tuning. The following hyperparameter tuning configuration values to get the optimal accuracy value can be seen in Table 3.

Table 3. Hyperparameter Tuning Configuration

Hyperparameter	Configuration	Best Parameters
hidden_layer_sizes	[(100,), (50,50), (30,20), (20,10)]	(50, 50)
activation	[‘relu’, ‘tanh’, ’logistic’]	relu
alpha	[0.0001, 0.001, 0.01, 0.1]	0.001
max_iter	[100, 500, 1000]	100

The results show that GridSearchCV hyperparameter tuning can improve the accuracy value well. GridSearchCV gets a good accuracy value of 82.37 with a precision value of 84.07, a recall value of 96.76, an F1-Score value of 89.97. It can be seen in the Confusion Matrix results from GridSearchCV that the model has a fairly good performance, but the high False Positive value also affects the model results because it predicts quite often that is not appropriate and the results obtained only have a slight

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difference, 20% of testing data with a total of 1,515 data will be evaluated using confusion matrix as shown in Fig 3.

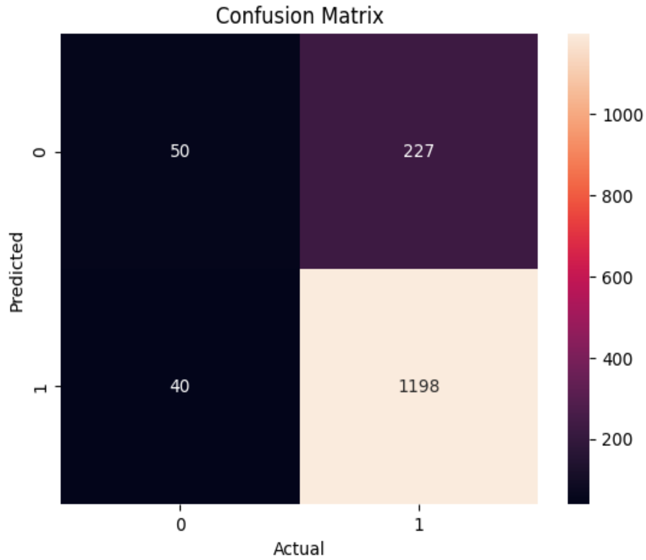

Fig. 3 Confusion Matrix with GridSearchCV

It is known that the FP value is greater than TP. This may occur due to unrepresentative data and class imbalance. The comparison of the number of positive classes is greater than the negative classes with the number of positive classes amounting to 6120 and negative classes amounting to 1452. Models that do not consider class imbalance may tend to optimize results on the majority class (positive) and pay less attention to the minority class (negative). This can also be influenced by the features used by the model being insufficient to differentiate between positive and negative classes which can lead to an increase in False Positive

Table 4. Evaluation Metrics

Model	**Accuracy (%)**	**Class**	**Precision (%)**	**Recall (%)**	**F1-Score(%)**
MLP + GridSearchCV	82.37	0	55.55	18.05	27.24
		1	84.07	96.76	89.97

Based on Table 4, it is known that the precision, recall and F1-Score values for class 0 get smaller accuracy than class 1. This means that the model that has been made is more accurate in predicting data that meets certain criteria for class 1 than class 0. So that it can cause a greater FP value than TN.

DISCUSSIONS

Research conducted for stunting classification using the MLP algorithm has proven to get a higher accuracy value than previous research that conducted stunting classification using the C4.5 algorithm (Yunus et al., 2023). The results of this study show the evolution of a more effective and accurate classification in identifying stunting cases. It can be seen in table 6 that overall, in terms of precision, recall, and accuracy, the table confirms that the MLP model is superior to the C4.5 model, indicating that the MLP model is more reliable in accurately predicting positive and negative cases as shown in Fig 4.

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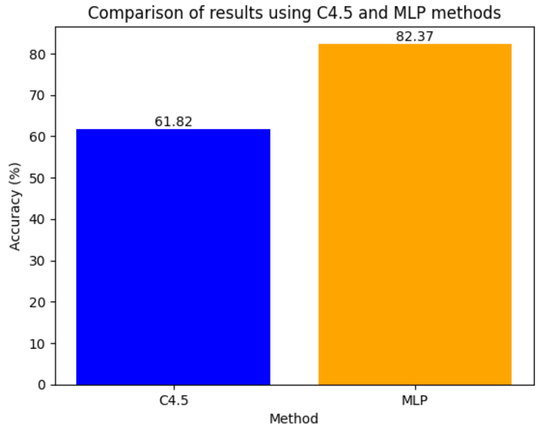

Fig. 4 Comparison of Results with Previous Research

The MLP algorithm can produce higher accuracy values than using the C4.5 algorithm, method used in previous research, because MLP has the ability to model data that has a complex structure better than the C4.5 algorithm and the use of MLP for classification on large datasets is superior to the C4.5 algorithm which can work well on small to medium datasets. In addition, the use of hyperparameter tuning in MLP also affects getting higher accuracy.

CONCLUSION

Based on research that has been conducted to classify stunting disease using the MLP method with GridSearchCV hyperparameter tuning, it produces a higher accuracy value of 82.37%. This shows that the MLP method is successful in classifying stunting diseases. However, it is important to continue to improve the model, dataset and other factors that affect the diagnosis in stunting disease to get more optimal results.

Due to the imbalance in the data held, the precision and recall values for one of the classes are still low, in the next research the smote or shap method will be added to get even better model performance.

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