VOL. 10. NO. 2 NOVEMBER 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480 /jitk.v10i2.5636

MULTICLASS CLASSIFICATION FOR STUNTING PREDICTION USING DEEP NEURAL NETWORKS

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Abstract — *Stunting is a chronic nutritional issue that hinders child growth and leads to serious long-term health and developmental impacts, particularly in developing countries. Therefore, early and accurate prediction of stunting is crucial for implementing effective interventions. This research aims to develop a multiclass classification model based on Deep Neural Networks (DNNs) to predict stunting status. The model is trained using a comprehensive dataset that encompasses various health variables related to stunting. The research process includes data collection, data preprocessing, dataset splitting, and training and evaluation of the DNNs model. The model can classify stunting status into four categories: stunted, severely stunted, normal, and tall. Further analysis is conducted to evaluate the influence of various parameters on the model's performance, including dataset splitting ratios (80:20 and 70:30) and learning rates (0.001, 0.0001, and 0.00001). The results show that a learning rate of 0.0001 yields the highest prediction accuracy, at 93.64% and 93.83% for the two data-splitting schemes. This indicates that this learning rate has achieved an optimal balance between convergence speed and the model's generalization capability. Additionally, the developed DNNs model can identify complex patterns hidden within the data without being affected by noise. These findings confirm that appropriate parameter selection, particularly the dataset splitting ratio and learning rate, can significantly enhance the DNNs model's ability to identify complex data patterns.*

Keywords: *deep neural networks, multiclass classification, prediction, stunting.*

Intisari— *Stunting adalah masalah gizi kronis yang menghambat pertumbuhan anak dan menimbulkan dampak kesehatan serta perkembangan jangka panjang yang serius, terutama di negara berkembang. Oleh karena itu, prediksi dini dan akurat terhadap stunting sangat krusial untuk pelaksanaan intervensi yang efektif. Penelitian ini bertujuan untuk mengembangkan sebuah model klasifikasi multi-kelas berbasis Deep Neural Networks (DNNs) untuk memprediksi status stunting. Model DNNs dilatih dengan dataset yang komprehensif, mencakup beragam variabel kesehatan yang relevan dengan stunting. Proses penelitian meliputi pengumpulan data, pra-pemrosesan data, pembagian dataset, serta pelatihan dan evaluasi model DNNs. Model DNNs mampu mengklasifikasikan status stunting ke dalam empat kategori, yaitu stunting, sangat stunting, normal, dan tinggi. Analisis lebih lanjut dilakukan untuk mengevaluasi pengaruh berbagai parameter terhadap kinerja model, termasuk proporsi pembagian dataset (80:20 dan 70:30) serta laju pembelajaran (0.001, 0.0001, dan 0.00001). Hasil penelitian menunjukkan bahwa laju pembelajaran sebesar 0.0001 mampu menghasilkan akurasi prediksi tertinggi, yakni 93.64% dan 93.83% pada kedua skema pembagian data. Hal ini mengindikasikan bahwa nilai laju pembelajaran tersebut telah mencapai keseimbangan optimal antara kecepatan konvergensi dan kemampuan generalisasi model. Selain itu, model DNNs yang dikembangkan juga mampu mengidentifikasi pola kompleks yang tersembunyi dalam data tanpa terpengaruh oleh noise. Temuan ini menegaskan bahwa pemilihan parameter yang tepat, khususnya proporsi pembagian dataset dan laju pembelajaran, dapat secara signifikan meningkatkan kemampuan model DNNs dalam mengidentifikasi pola data yang kompleks*

Kata Kunci: *deep neural networks, klasifikasi multikelas, prediksi, stunting.*

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VOL. 10. NO. 2 NOVEMBER 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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INTRODUCTION

Stunting, a growth disorder prevalent in toddlers, is characterized by short stature due to chronic malnutrition and inadequate nutrient intake [1],[2],[3]. Factors contributing to stunting include insufficient maternal knowledge on nutrition, poor feeding practices, lack of access to clean water, and limited healthcare services [1],[2],[3]. Studies emphasize the importance of exclusive breastfeeding, quality complementary feeding, infectious disease prevention, maternal education, and effective parenting in reducing stunting rates among children under five [2]. Stunting not only impacts physical growth but also cognitive development [4].

This issue is a major concern in public health, especially in developing countries where the prevalence of stunting remains high. According to the World Health Organization (WHO), millions of children worldwide suffer from stunting, leading to reduced physical and intellectual potential. Stunting affects learning abilities, adult productivity, and increases the risk of chronic diseases [5]. Therefore, early detection and effective interventions are crucial to prevent the long-term impacts of stunting.

Several previous studies have focused on predicting stunting. Ndagijimana et al. [6] used machine learning to predict stunting in toddlers in Rwanda, achieving an accuracy of 80.49%. Yunus et al. [7] employed the C4.5 algorithm and anthropometric data for stunting classification in toddlers, with an accuracy of 61.82%. Amin et al. [8] used anthropometric data and Long Short-Term Memory to identify stunting in toddlers, achieving an accuracy of 81.53%. Chilyabanyama et al. [9] classified stunting in children under five in Zambia using several machine learning methods, including logistic regression, random forest, SVC, XG Boost, and Naïve Bayes, with the highest accuracy of 79% for the Random Forest method.

Although previous studies have shown the potential of machine learning in predicting stunting, there are some limitations of using a binary classification that only distinguishes between stunted and non-stunted children and the accuracy of the model still needs to be improved. To address this issue, this study focuses on developing a multiclass classification model for stunting prediction in toddlers using Deep Neural Networks (DNNs). DNNs have shown significant potential in various classification tasks due to their ability to automatically learn complex features from raw data [10]. Unlike traditional machine learning algorithms, DNNs can capture hierarchical representations of data through multiple layers of nonlinear transformations, making them highly effective for image and pattern recognition tasks [11]. This characteristic is particularly useful in health-related applications where complex and high-dimensional data are common.

Furthermore, DNNs have been successfully applied in medical diagnostics, demonstrating superior performance compared to conventional methods. For instance, in image-based diagnostic tasks, DNNs have achieved remarkable accuracy for medical image analysis [12]. Agrawal et al. [13] used DNNs for brain tumor classification on an unbalanced dataset, effectively classifying tumor types. %. Kumar et al. [14] used DNNs for multi-class stress detection and achieved an accuracy of 96.87%. Aljuaid et al. [15] performed multi-class classification on breast cancer using DNNs and achieved an average accuracy of 97.81%. Purni and Vedhapriyavadhana [16] used DNNs for enhanced multi-class skin cancer classification and achieved an average accuracy of 99.00%. Kumar and Ramachandran [17] used DNNs for multi-class ECG signal processing and classification and achieved an average accuracy of 99.33%. DNNs have also been widely used in various classification tasks such as Alzheimer's disease classification [18], dental implant classification [19], retinal fundus image classification [20]. The ability of DNNs to process and learn from large-scale data enables the extraction of subtle patterns that simpler models might miss [21].

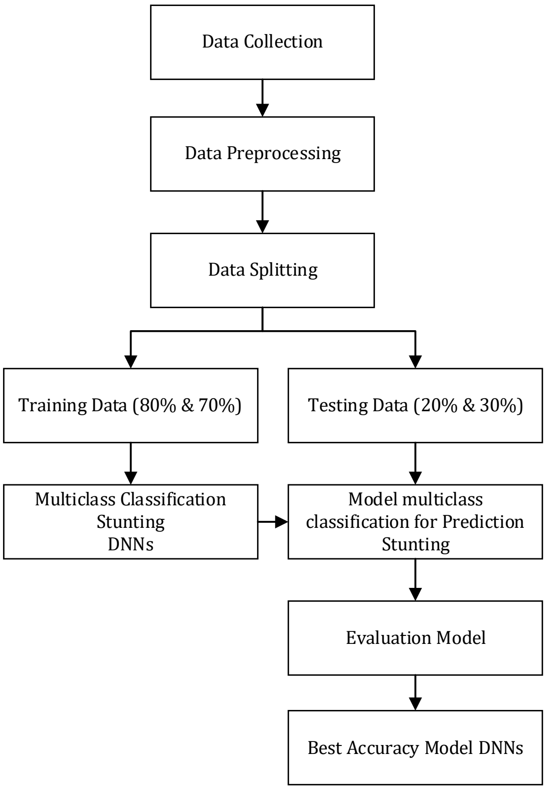
Based on the above problems, the main purpose and contribution of this research is to overcome the limitations of previous research that only focuses on binary stunting classification by developing a multi-class classification model that is more accurate in predicting the severity of stunting using Deep Neural Networks (DNNs). To enhance the accuracy of stunting multiclass classification, this research optimizes hyperparameters, particularly the learning rate, and evaluates model performance using various dataset splitting schemes. By effectively optimizing the learning rate, this study aims to improve the DNN model's performance in stunting prediction, thereby making a significant contribution to early detection and intervention efforts for stunting.

MATERIALS AND METHODS

This research employs a quantitative experimental approach aimed at developing and testing the performance of a multi-class stunting classification model using Deep Neural Networks (DNNs). The research process is divided into several key stages, including data collection, data

P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480 /jitk.v10i2.5636

preprocessing, DNNs model development, hyperparameter optimization, and performance evaluation with various dataset splitting schemes. Figure 1 illustrates the research methodology employed to develop the multiclass classification model for stunting prediction using DNNs.



Source: (Research Results, 2024)
Figure 1. Research Methodology

1. Data Collection

The data used in this research is a secondary dataset sourced from https://www.kaggle.com/datasets/rendiputra/stunting-balita-detection-121k-rows [22]. The stunting toddler detection dataset is specifically designed to identify stunting cases in toddlers based on World Health Organization (WHO) standards. This dataset comprises 121,000 entries, detailing information on age, gender, height, and nutritional status of toddlers (stunted = 13815, severely stunted = 19869, normal = 67755, tall = 19560).

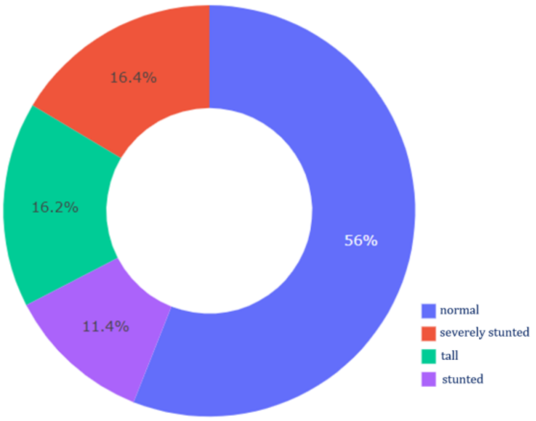
a. Age (Month): A toddler's age expressed in months. When assessing a child's growth phase and comparing it to healthy growth standards, this age range is crucial.
b. Gender: The categories "male" and "female" are present in this column. When examining development trends and the possibility of stunting, gender is a significant determinant.
c. Height (centimeters), height is an important metric for evaluating a kid under five years old's physical development. Researchers can use this data to assess if a child's growth is typical for their age. Table 1 provides the details of the dataset used.

Table 1. Detail of Stunting Dataset

No	Age (Month)	Sex	Body Height (cm)	Status
0	0	1	45	stunted
1	0	1	57	tall
2	0	1	47	normal
3	0	1	48	normal
4	0	1	43	severely stunted
...	...	...	...	...
120994	60	2	101	normal
120995	60	2	98	stunted
120996	60	2	121	normal
120997	60	2	112	normal
120998	60	2	110	normal

Source: (Research Results, 2024)

Figure 2 shows the number of data points for each class of stunting status.



Source: (Research Results, 2024)
Figure 2. Presentation of Stunting Status

2. Data Preprocessing

Data preprocessing is a critical step in ensuring the quality and integrity of the data before further analysis. This stage includes several essential steps that support the validity of the research results. First, the process begins with checking for missing values to identify and handle any absent data. This is crucial because incomplete data can lead to biased or inaccurate conclusions.

The next step is data type conversion to ensure that each attribute or variable is in the appropriate format for statistical and computational analysis. Following this, data normalization is performed to ensure all values fall within a uniform range, facilitating more accurate comparison and integration of data across the dataset. This process not only improves the data distribution but also ensures the reliability of the resulting analysis.

VOL. 10. NO. 2 NOVEMBER 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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3. Data Splitting

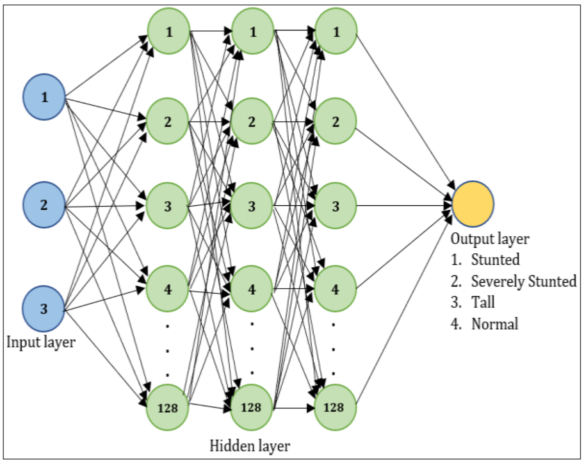
The process of splitting the dataset is a crucial step in preparing data for model training and evaluation. In this research, two scenarios were implemented for splitting the dataset to train and test the DNNs model for multiclass stunting prediction.

a. Scenario 1: The dataset is divided into 80% for model training and 20% for model evaluation.
b. Scenario 2: The dataset is divided into 70% for model training and 30% for model evaluation.

These proportions provide more data for model training, which can enhance the model's performance by offering greater data variety.

4. Multiclass Classification Stunting Model

Deep Neural Networks (DNNs) are artificial neural networks with the ability to learn complex relationships in data through a layered architecture consisting of several hidden layers between the input and output. Each layer comprises numerous neurons connected to neurons in the preceding and subsequent layers, forming a complex network. Figure 3 illustrates the DNNs architecture built in this research.



Source: (Research Results, 2024)

Figure 3. Multiclass Classification for Stunting Prediction DNNs Architecture

In developing a DNNs model for multiclass classification in stunting prediction, several key parameters must be optimized. The DNNs parameters used in this study are as follows:

a. Input layer with an input shape adjusted to the input data, which has 3 features.
b. Three hidden layers.
c. The number of neurons used is 128 in both the input and hidden layers.
d. The activation function used in the input and hidden layers is ReLU to handle non-linearity and enable the model to learn complex and intricate patterns.
e. The activation function in the output layer is softmax with 4 neurons, corresponding to the number of predicted classes. The softmax activation function is used to convert the output into class probabilities.
f. The regularization methods used are L2 at 0.01 and Dropout at 0.3 to reduce the risk of overfitting by adding a penalty to the model complexity and randomly dropping out a number of neurons during training.
g. The optimization algorithm used is Adam for its ability to adaptively adjust the learning rate, accelerate convergence, and improve training stability.
h. The learning rates used are 0.001, 0.0001, and 0.00001.
i. The loss function used is categorical cross entropy, which is commonly used for multiclass classification.
j. The evaluation metrics for the model are accuracy and precision.
k. The batch size used is 64.
l. The number of epochs/iterations for training is 100.

5. Model Evaluation

Model evaluation is a crucial step in measuring the performance of a deep learning model. In this study, the model evaluation was conducted by examining the accuracy, precision, and loss values generated by the multiclass classification stunting DNNs model tested using the testing data. Formula (1) is the formula for calculating accuracy, and Formula (2) is the formula for calculating precision.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$precision = \frac{TP}{TP+FP} \quad (2)$$

where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

RESULTS AND DISCUSSION

The outcomes from each phase of developing the multiclass classification model for stunting prediction using DNNs are presented below.

1. Data Preprocessing Results

The first step in data preprocessing was checking for missing values. Figure 4 shows that the dataset used does not contain any missing values.

```
df.isnull().sum()

Age (Month)        0
Sex                0
Body Height (cm)   0
Status             0
dtype: int64
```

Source: (Research Results, 2024)
Figure 4. Check for Missing Values

The next step was converting object data types to numeric formats to ensure they were suitable for model development. In this process, data type conversion is performed on the variables "Gender" where 1 = male, 2 = female and "Nutritional Status" where 3 = high, 2 = stunted, 0 = normal, 1 = severely stunted. Figure 5 illustrates this data type conversion process.

```
df["Sex"] = df["Sex"]. map({"male ": 1, "female": 2})

s = (df.dtypes == 'object')
cat_col = list(s[s].index)
cat_col

for i in cat_col:
 lb = LabelEncoder()
 df[i] = lb.fit_transform(df[i])
```

Source: (Research Results, 2024)
Figure 5. Data Type Conversion

The final step in data preprocessing involved normalizing the data using StandardScaler. StandardScaler is a widely used tool in machine learning preprocessing that standardizes features to have a mean of zero and a standard deviation of one. Figure 6 shows the data normalization process.

```
X.drop(['Status'],axis = 1,inplace = True)
Scaler = StandardScaler(copy=True , with_mean=True,
          with_std=True)
X = Scaler.fit_transform(X)
```

Source: (Research Results, 2024)
Figure 6. Data Normalization

Table 2 presents the normalized data results.

Table 2. Result of Normalization Dataset

No	Age (Month)	Sex	Body Height (cm)	Status
0	-1,7168548	-1,00834064	-2,54688462	stunted
1	-1,7168548	-1,00834064	-1,84673536	tall
2	-1,7168548	-1,00834064	-2,41559775	normal
...	...	...	...	...
120996	1,69707641	0,99172836	1,88686819	normal
120997	1,69707641	0,99172836	1,36088477	normal
120998	1,69707641	0,99172836	1,22216386	normal

Source: (Research Results, 2024)

2. Data Splitting Results

The preprocessed data was subsequently divided into two scenarios: 80:20 and 70:30, as shown in Table 3.

Table 3. Data Splitting Results

Skenario	Training	Testing
80 : 20	96800	24200
70 : 30	84700	36300

Source: (Research Results, 2024)

The dataset was randomly split into training and testing sets.

3. Modelling and Evaluation Results

This research focuses on developing a multiclass classification model for predicting stunting in toddlers using DNNs. A critical step in this development is the optimization of hyperparameters, particularly the learning rate, and evaluating the model's performance based on different dataset splits. The learning rate is a crucial parameter that determines the step size for weight updates during training.

In this research, experiments were conducted with three different learning rates: 0.001, 0.0001, and 0.00001. The right learning rate helps the model learn more effectively by identifying relevant patterns in the data. Additionally, the dataset was split in ratios of 80:20 and 70:30 for each learning rate to assess the impact of training and testing data size on model performance.

a. Model Development and Evaluation Results with 80:20 Dataset Split

The training and testing results for the model multiclass classification of stunting prediction with DNNs using the 80:20 dataset split are shown in Tables 4, 5, and Figure 7.

Table 4. Training Results (80:20 Dataset Split)

Learning Rate	Accuracy (%)	Precision (%)
0.001	91.50	93.51
0.0001	**93.67**	**95.53**
0.00001	93.49	95.46

Source: (Research Results, 2024)

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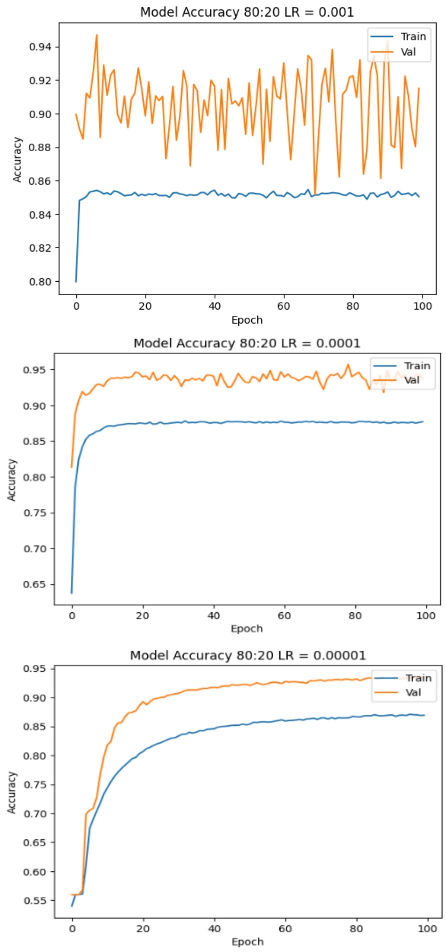
VOL. 10. NO. 2 NOVEMBER 2024
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v10i2.5636

Table 5. Testing Results (80:20 Dataset Split)

Learning Rate	Accuracy (%)	Precision (%)
0.001	91.43	93.44
0.0001	**93.64**	**95.48**
0.00001	93.55	95.47

Source: (Research Results, 2024)



Source: (Research Results, 2024)
Figure 7. Chart of Training Accuracy Results (80:20 Dataset Split)

Based on Tables 4 and 5, and Figure 7, it was found that learning rates of 0.0001 and 0.00001 provide more stable performance with better accuracy and precision in the 80:20 dataset split, both during training and testing phases. The controlled fluctuations in loss values indicate a more stable training process, minimizing the risk of overfitting.

b. Model Development and Evaluation Results with 70:30 Dataset Split

The training and testing results for the model multiclass classification of stunting prediction with DNNs using the 70:30 dataset split are shown in Tables 6, 7, and Figure 8.

Table 6. Training Results (70:30 Dataset Split)

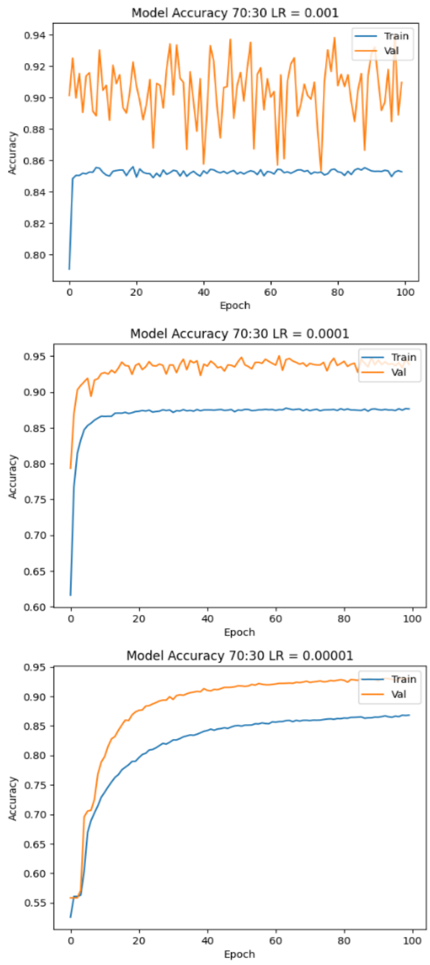
Learning Rate	Accuracy (%)	Precision (%)
0.001	90.95	92.68
0.0001	**94.07**	**95.74**
0.00001	93.17	95.20

Source: (Research Results, 2024)

Table 7. Testing Results (70:30 Dataset Split)

Learning Rate	Accuracy (%)	Precision (%)
0.001	90.96	92.71
0.0001	**93.83**	**95.55**
0.00001	93.11	95.15

Source: (Research Results, 2024)



Source: (Research Results, 2024)
Figure 8. Chart of Training Accuracy Results (70:30 Dataset Split)

Based on Tables 6 and 7, and Figure 8, it was found that learning rates of 0.0001 and 0.00001 provide more stable performance with better accuracy and precision in the 70:30 dataset split, both during training and testing phases. The controlled fluctuations in loss values indicate a more stable training process, minimizing the risk of overfitting.

Based on the results obtained, a learning rate of 0.0001 achieved the highest accuracy in both dataset splitting schemes, with an accuracy of 93.64% for the 80:20 split and 93.83% for the 70:30 split during testing. These findings indicate that the resulting DNN models can predict multiclass stunting status more effectively than previous studies. Table 8 shows a comparison of accuracy with previous research.

Table 8. Comparison of Accuracy with Previous Research.

Methods	Task	Accuracy(%)
Machine Learning	Binary Classification	80,49
C4.5	Binary Classification	61,82
LSTM	Binary Classification	81,53
Random Forest	Binary Classification	79
Deep Neural Networks	**Multi-Class Classification**	**93,83**

Source: (Research Results, 2024)

The results show that the right learning rate helps DNN models learn more effectively by identifying relevant patterns in the data. This improved accuracy in stunting classification is expected to enable more targeted interventions, better resource allocation, and ultimately, improved health outcomes for children affected by stunting.

CONCLUSION

This research develops a multiclass classification model for stunting prediction in toddlers using Deep Neural Networks (DNNs), with a focus on learning rate optimization and performance evaluation based on different dataset shares. The test results show that learning rate optimization is very important to improve the performance of DNNs models. Learning rates of 0.0001 provide optimal performance with the highest accuracy and precision in the 80:20 and 70:30 dataset sharing scenarios. This learning rate also showed better training stability with controlled fluctuations in loss values, reducing the risk of overfitting. This research also demonstrates that the DNNs method outperforms the approaches used in previous research. Further evaluation and additional experiments with other hyperparameter combinations can be conducted to further optimize the accuracy and precision of the model.

ACKNOWLEDGMENTS

We extend our deepest gratitude to Universitas Mikroskil and the Directorate of Research, Technology, and Community Service (DRTPM) under the Ministry of Research, Technology, and Higher Education of the Republic of Indonesia for their invaluable support, both material and immaterial, throughout this research. Their assistance has been instrumental in enabling us to conduct our research effectively, with the goal of contributing to societal well-being and advancing scientific knowledge.

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P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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