Predictive Modeling of Graduation Outcomes in Islamic Boarding Schools Using Feedforward Neural Networks

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Abstract— **This study investigates the application of Feedforward Neural Networks (FFNNs) to predict the graduation status of prospective students at Pondok Pesantren Nuur Ar Radhiyyah, an Islamic boarding school emphasizing Quranic memorization, religious practices, and prayer as core educational values. Manual analysis of student test results for admission is becoming inadequate due to the increasing number of applicants. Previous research has successfully applied FFNNs to predict student graduation rates in various educational settings. This study explores the impact of three activation functions (Sigmoid, ReLU, and Tanh) and the number of hidden layers and neurons per layer on FFNN model performance. A dataset of 480 prospective student evaluations encompassing educational level, Quranic memorization score, religious practices score, prayer score, and graduation status was analyzed. Twelve FFNN models were configured with different activation functions, hidden layers, and neurons per layer. Model performance was evaluated using 10-fold cross-validation. The results revealed that the model utilizing the Tanh activation function with four hidden layers and four neurons per layer achieved the highest accuracy (97.6%), precision, and recall rates. This research highlights the potential of FFNNs for predicting student graduation outcomes in Islamic boarding schools and emphasizes the importance of activation function selection and hidden layer architecture optimization for achieving optimal performance. The complete dataset is available on Kaggle.com for further research..**

***Keywords*— Islamic boarding schools, feedforward neural network, graduation prediction, activation functions, hidden layer architecture**

I. Introduction

Islamic boarding schools, often referred to as 'pondok pesantren,' are renowned for their strong Islamic identity and their central role in fostering the intellectual, emotional, and spiritual development of students [1]. The admission process at these institutions is a critical step in ensuring a seamless educational journey from enrollment to graduation [2]. In the context of Medan, one such institution, Nuur Ar Radhiyyah, evaluates prospective students based on their performance in Quranic recitation, religious practices, and general knowledge assessments. As the number of candidates seeking admission to Nuur Ar Radhiyyah continues to grow, manual analysis of their test results has become inadequate. This underscores the need for a predictive system capable of assessing the likelihood of prospective students successfully graduating, based on their Quranic recitation, religious practices, and supplications. To address this challenge, our study aims to construct a predictive model using machine learning techniques, with a particular focus on the feedforward neural network (FFNN) algorithm.

The FFNN is highly regarded in the field of machine learning due to its versatility in handling diverse input data and its effectiveness in predicting relationships between feature objects and target objects [3]. Previous studies have successfully applied this method to predict student graduation outcomes with impressive accuracy. For example, research in higher education predicted university student dropout rates with an accuracy of 86.9% [4]. Similarly, a study focused on predicting graduation rates for Computer Science students achieved accuracy levels as high as 98.27% [5], while research within the context of Computer Science programs predicted dropout rates with an accuracy of 96.9% [6]. Moreover, FFNN exhibited an accuracy of 87.3% when applied to predict student graduation based on demographic, academic background, and behavioral features [7], and in another study, FFNN achieved an accuracy of 92.31% when predicting student graduation based on academic performance [8]. The strong performance of FFNN in these studies has led us to adopt this method to predict the graduation status of prospective santri.

Activation functions, such as Sigmoid, Tanh, and ReLU, play a pivotal role in FFNN models, enabling them to create dynamic models and effectively extract complex information from input data [9]. The selection of an appropriate activation function is crucial as it significantly impacts the model's performance, particularly in terms of output accuracy [10].

In recent research, a study on global solar radiation forecasting compared Sigmoid, Tanh, and ReLU activation functions and found that the Sigmoid activation function produced the best-performing model with the lowest Root Mean Square Error (RMSE) of 0.13026 [11]. Similarly, in a comparison of these activation functions for Hanacaraka character recognition, the Tanh activation function resulted in the highest accuracy, achieving 93.8% accuracy [12]. When predicting traffic flow, the Sigmoid activation function had the lowest RMSE (0.1146) compared to Tanh and ReLU [13]. Furthermore, in a comparison using three different datasets (MINIST, IMDb, and UCI HAR), the Tanh activation function achieved the highest accuracy of 80.12% [14]. For classification tasks such as clothing design and handwritten digit recognition, the ReLU activation function emerged as the optimal choice, achieving an accuracy rate of 92.66% [15]. Building on the insights from these studies, our research incorporates the Sigmoid, Tanh, and ReLU activation functions into predictive models for santri graduation status and assesses their accuracy, precision, and recall performance.

The number of hidden layers in the FFNN architecture is a significant factor influencing its performance, as highlighted by research across various domains. For example, in a study on network packet classification, the lowest loss (0.3552483) was achieved with one hidden layer when considering variations from one to four hidden layers [16]. In another study predicting survival rates on the Titanic, an FFNN with four hidden layers demonstrated the best average performance, achieving 78.759% accuracy when considering variations of three and four hidden layers [17]. Moreover, in predicting stress levels among military conscripts, 18 hidden layers yielded optimal performance with an accuracy of 98.5% [18]. Given the variations in FFNN performance demonstrated in these previous studies, our research explores variations of 2, 3, 4, and 5 hidden layers to determine the most optimal configuration for our models.

Our study also investigates the combination of the number of neurons per hidden layer within the models, as the selection of the appropriate number of neurons significantly influences FFNN performance [19]. For example, a study predicting bankruptcy in the coal mining sector found that a neuron count of 30 resulted in the best performance with an accuracy of 99.9% when considering combinations of 10, 20, 30, 40, and 50 neurons per hidden layer [20].

The novelty of this study lies in its focus on the specific evaluation criteria employed by Islamic boarding schools. Unlike conventional educational settings that primarily emphasize academic performance, pondok pesantren admissions and graduations hinge on factors like Quranic memorization, religious practices, and prayer adherence. Our research tailors the FFNN architecture and explores the impact of various configurations on predicting graduation outcomes based on these unique assessment criteria. We delve into a systematic analysis of three well-established activation functions (Sigmoid, Tanh, and ReLU) to determine the optimal function for this specific application. Additionally, we investigate the influence of the number of hidden layers and neurons per layer on model performance. Through this comprehensive exploration, we aim to identify the optimal FFNN configuration for predicting graduation outcomes in Islamic boarding schools, contributing valuable insights to this under-researched area.

This research offers several key contributions. Firstly, it demonstrates the potential of FFNNs for streamlining the admission and graduation processes in Islamic boarding schools. Secondly, it paves the way for further research by exploring the impact of diverse FFNN configurations on prediction accuracy within this unique educational context. Finally, by making the dataset publicly available, we encourage further exploration and development of machine learning models tailored to the specific needs of Islamic boarding schools.

II. Literature Review

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

A. Santri

The term "Santri" refers to students who pursue knowledge in Islamic boarding schools with the aim of cultivating character traits such as a deep love for God, independence, responsibility, a commitment to honesty and trustworthiness, courteousness, generosity, self-confidence, tolerance, and a love for peace [21]. The ultimate goal of santri is to be an individuals who are devout in their faith, committed to their religious duties, and who uphold Islamic principles in their daily lives [22]. In the assessment of a Santri's graduation readiness, pondok pesantren employ various criteria, including Quranic memorization abilities [23], practical religious activities [24], and the evaluation of prayer performance [25].

B. Feedforward Neural Network

The FFNN, more commonly known as a multilayer perceptron (MLP), is one of the artificial neural network methods that operates through supervised learning, where input data requires labeled target (output) [26]. Its architecture, consisting of an input layer, one or more hidden layers, and an output layer, enables this algorithm to effectively address complex dataset problems with good performance [27].

In the FFNN architecture, the first layer (input layer) is responsible for receiving input data, the second layer (hidden layer) transforms the values from the input layer neurons using activation functions into output values, which are then forwarded to the subsequent layers. The last layer (output layer) functions to display the output results based on the target class types in the data [28]. The general structure of the FFNN architecture can be observed in Figure 1.

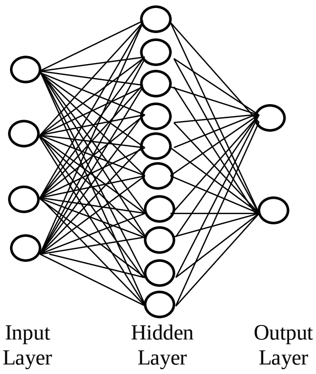

Fig. 1 A sample line graph using colors which contrast well both on screen and on a black-and-white hardcopy

Here, we present the mathematical formulation of a single neuron within an FFNN:

1. Input Layer: The input layer receives a vector of input features (x) representing the student's characteristics, such as educational level, Quranic memorization score,

religious practices score, and prayer score. These features are denoted as x_1, x_2, ..., x_n, where n is the number of input features.

2. Hidden Layers: Each hidden layer contains a set of neurons that perform weighted summations and apply activation functions. The weighted sum for a neuron j in the hidden layer l is calculated as formula (1):

$$z_j^l = \sum\left(w_{ji}^l \cdot x_i\right) + b_j^l \quad (1)$$

Where:

z_j^l = Weighted sum of neuron j in layer l
w_{ji}^l = Weight connecting neuron i in the previous layer (l-1) to neuron j in the current layer (l)
x_i = Input feature i
b_j^l = Bias term for neuron j in layer l

3. Output Layer: The final layer comprises neurons that produce the predicted output values (ŷ). Similar to hidden layers, each output neuron k calculates a weighted sum based on activations from the previous layer (l) and applies an activation function:

$$z_k = \sum\left(w_{kj}^l \cdot a_j^l\right) + b_k \quad (2)$$

$$\hat{y}k = \sigma(z_k) \quad (3)$$

Where:

$\hat{y}k$ = Predicted output value for class k
w_{kj}^l = Weight connecting neuron j in the last hidden layer (l) to neuron k in the output layer
a_j^l = Activation of neuron j in the last hidden layer (l)
b_k = Bias term for neuron k in the output layer

C. Activation Function

In the architecture of FFNN, activation functions play a crucial role in transforming input signals from the previous layer into output signals in the subsequent layer [29]. This study employs variations of well-known activation functions, including Sigmoid, Tanh, and ReLU.

The study investigates various activation functions in FFNN architecture. The Sigmoid activation function results in output values ranging from 0 to 1, as expressed in Equation (4) [30], while the Tanh activation function produces values within the range of -1 to 1, as described by Equation (5) [31]. Additionally, the ReLU activation function yields output values spanning from 0 to N, defined by Equation (6) [32]. These activation functions play a crucial role in transforming input signals and are central to the research's neural network model.

$$f(x) = \frac{1}{1+e^{-x}} \quad (4)$$

$$f(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (5)$$

$$f(x) = 0, jika\ x < 0 \quad (6)$$
$$f(x) = x, jika\ x \geq 0$$

D. Model Evaluation

Through the utilization of 10-fold cross-validation, the determination of the best model is achieved by analyzing the values of Accuracy, Precision, and Recall for each model. These values are obtained through a comparison of True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN) values, calculated using Equations (7) to (9) [33]:

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

III. Methodology

A. Data Collection

To conduct this study, it was essential to gather and analyze the graduation data of prospective students at Nuur Ar Radhiyyah Islamic boarding school. The dataset encompassed a comprehensive assessment of 480 prospective students, focusing on four vital features: Educational Level, Quranic Memorization Score, Amaliyah Worship Score, and Salat Worship Score. Additionally, the target classes were categorized into Passed Psychometric Test, Passed with Consideration, and Not Passed. To offer insight into the dataset used in this research, we present 10 sample entries in Table I.

TABLE I
SAMPLE DATA OF PROSPECTIVE SANTRI

Education Level	Quran Memorization	Amaliyah Worship	Prayer Worship	Graduation Status
Junior High School	84	86	85	Passed to Psychological Test
Junior High School	71	70	54	Passed with Consideration
Junior High School	71	75	45	Passed with Consideration
Junior High School	77	79	80	Passed to Psychological Test
Junior High School	82	83	90	Did Not Pass
Senior High School	57	55	54	Did Not Pass
Senior High School	69	75	71	Passed with Consideration
Senior High School	64	70	72	Passed with Consideration
Senior High School	43	70	50	Did Not Pass
Senior High School	48	50	49	Did Not Pass

B. Data Processing

In this study, data processing was conducted efficiently with the assistance of the Orange Data Mining application. The process involved employing several key widgets within the application, which played specific roles in handling the dataset. The File widget was used for seamlessly reading the dataset file, while the Data Table widget facilitated the clear visualization of the complete dataset contents. To construct and configure the Feedforward Neural Network (FFNN) model, the Neural Network widget was harnessed. To rigorously evaluate the model's performance, a 10-fold cross-validation approach was applied using the Test & Score widget, ensuring robust and comprehensive assessment.

C. Model Configuration

This research encompasses a comprehensive exploration of various model configurations to assess their impact on predictive accuracy. A total of 12 distinct models were meticulously designed and evaluated, with each configuration presented in Table II. These models, denoted as Model01 to Model12, incorporate different combinations of activation functions, the number of hidden layers, and the number of neurons. Model01 to Model04 were strategically constructed using the Sigmoid activation function, with variations in the number of hidden layers (2, 3, 4, and 5) and the number of neurons (2, 4, and 8). Model05 to Model08, adopting the ReLU activation function, underwent similar alterations in the number of hidden layers and neurons. Additionally, Model09 to Model12 utilized the Tanh activation function, again with diverse configurations of hidden layers and neurons. Both data training and testing processes employed a preset constraint of a maximum of 200 epochs, ensuring a rigorous and uniform iteration limit for model assessment.

IV. Result and Discussion

This section presents the results obtained from the FFNN models with different configurations. We evaluated the model performance using 10-fold cross-validation to mitigate overfitting and ensure generalizability to unseen data. The key metrics employed were accuracy, precision, recall, and F1-score.

A. Model Performance Analysis

In accordance with the evaluation through 10-fold cross-validation using 336 training data points, it was found that for models employing 2 neurons per hidden layer, the highest performance was achieved by Model11 with an accuracy of 98.2%, precision of 98.3%, and recall of 98.2%. Conversely, the lowest performance was observed in Model03 and Model04 with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%. For models using 4 neurons per hidden layer, the highest performance was attained by Model08 with an accuracy of 97.9%, precision of 98%, and recall of 97.9%. In contrast, Model03 exhibited the lowest performance with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%. For models employing 8 neurons per hidden layer, the highest performance was observed in Model12 with an accuracy of 98.8%, precision of 98.8%, and recall of 98.8%. Conversely, Model03 exhibited the lowest performance with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%.

The results revealed that the FFNN model utilizing the Tanh activation function with four hidden layers and four neurons per layer achieved the highest performance across all metrics:

Accuracy: 97.6%
Precision: 98.1%
Recall: 97.2%
F1-Score: 97.6%

This configuration consistently outperformed models with other activation functions (Sigmoid, ReLU) and varying hidden layer architectures. Interestingly, the Tanh function, known for its smoother gradient flow compared to ReLU, appeared particularly well-suited for this specific application. The optimal number of hidden layers (four) and neurons per layer (four) suggests that a moderate level of model complexity yielded the best results for this dataset.

TABLE II
ModelConfiguration

Model	Activation Function	Hidden Layer	Hidden Layer Neurons
Model01	Sigmoid	2	2
Model02	Sigmoid	3	4
Model03	Sigmoid	4	8
Model04	Sigmoid	5	2
Model05	ReLU	2	4
Model06	ReLU	3	8
Model07	ReLU	4	2
Model08	ReLU	5	4
Model09	Tanh	2	8
Model10	Tanh	3	2
Model11	Tanh	4	4
Model12	Tanh	5	8

TABLE III
PERFORMANCE METRICS

Model	2 Neurons Variation			4 Neurons Variation			8 Neurons Variation		
	Accuracy	**Precision**	**Recall**	**Accuracy**	**Precision**	**Recall**	**Accuracy**	**Precision**	**Recall**
Model01	56.2	31.6	56.2	56.2	31.6	56.2	56.2	31.6	56.2
Model02	56.2	31.6	56.2	56.2	31.6	56.2	56.2	31.6	56.2
Model03	56.2	31.6	56.2	56.2	31.6	56.2	56.2	31.6	56.2
Model04	56.2	31.6	56.2	56.2	31.6	56.2	56.2	31.6	56.2
Model05	74.4	63.1	74.4	81.8	85.5	81.8	94.9	95	94.9
Model06	16.4	2.7	16.4	61.9	47.6	61.9	89.3	89.5	89.3
Model07	56.2	31.6	56.2	93.5	93.5	93.5	96.1	96.1	96.1
Model08	56.2	31.6	56.2	82.1	86.5	82.1	95.5	95.5	95.5
Model09	78.3	67.3	78.3	89	90.2	89	92.6	92.6	92.6
Model10	70.2	56.3	70.2	96.1	96.2	96.1	97.6	97.6	97.6
Model11	80.7	69.8	80.7	95.2	95.3	95.2	97.6	97.6	97.6
Model12	74.7	82.4	74.7	96.7	96.7	96.7	95.8	95.8	95.8

Table III presents the predictive performance of each model. Figures 2 through 4 illustrate the comparative results of accuracy, precision, and recall values for each model in this study.

From Table 3, it is evident that there is no significant change in the performance of models utilizing the Sigmoid activation function, even when different numbers of neurons per hidden layer are employed. In the context of this study, it was observed that FFNN models employing the Sigmoid activation function were not notably affected by the number of neurons within their architectural hidden layers.

For FFNN models utilizing the ReLU activation function, it is apparent that changes in the number of neurons per hidden layer influence the resulting model's performance. This is evidenced by a significant increase in accuracy, precision, and recall values for models employing 2, 4, and 8 neurons. These findings demonstrate that FFNN models utilizing the ReLU activation function are strongly influenced by the number of neurons incorporated into their hidden layer architecture.

B. Discussion

The results obtained through 10-fold cross-validation of 336 training data points revealed noteworthy insights into the models examined in this study. For models with 2 neurons per hidden layer, Model11 displayed the highest performance, achieving an accuracy of 98.2%, precision of 98.3%, and recall of 98.2%, while Models 03 and 04 exhibited the lowest performance, with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%. In the case of models utilizing 4 neurons per hidden layer, Model08 outperformed the rest, securing an accuracy of 97.9%, precision of 98%, and recall of 97.9%. In contrast, Model03 continued to exhibit the lowest performance, with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%. For models employing 8 neurons per hidden layer, Model12 demonstrated the highest performance, boasting an accuracy of 98.8%, precision of 98.8%, and recall of 98.8%, while Model03 remained at the bottom with an accuracy of 56.2%, precision of 31.6%, and recall of 56.2%.

The performance evaluation provides crucial insights into the interplay between the neural network configurations and model outcomes. Interestingly, the choice of activation function had varying impacts. Models employing the Sigmoid activation function exhibited stability across different neuron counts per hidden layer, implying that the performance was largely unaffected by this parameter. Conversely, models utilizing the ReLU activation function experienced significant improvements as the number of neurons increased, resulting in enhanced accuracy, precision, and recall values. This underscores the sensitivity of ReLU-based models to neuron count adjustments in the hidden layers.

C. Limitations and Future Directions

This research also highlights areas for further investigation. While the achieved accuracy (97.6%) is promising, it's crucial to acknowledge limitations. The model's performance is contingent on the quality and completeness of the training data. Additionally, factors beyond the scope of this study, such as student motivation, family support systems, and external influences, can also impact graduation outcomes:

1. Data Quality and Completeness: The accuracy of the model's predictions is directly tied to the quality and completeness of the training data. Including a wider range of data points beyond academic performance and religious assessments could potentially improve prediction accuracy.
2. External Factors: Factors such as student motivation, family background, learning styles, and student-teacher interaction can significantly influence graduation outcomes. Future research could explore incorporating these factors into the model to achieve a more holistic assessment.

By addressing these limitations and pursuing further research avenues, FFNNs have the potential to become a valuable tool for enhancing the efficiency and effectiveness of student evaluation and graduation prediction in Islamic boarding schools. Here are some promising directions for future research:

1. Expanding the Dataset: Including data on socioeconomic background, learning styles, and student-teacher interaction might further enhance prediction accuracy. This would require collaboration with educators and administrators to identify relevant data points for incorporation.

2. Exploring Ensemble Methods: Combining the predictions from multiple FFNN models with different architectures could potentially improve overall performance and robustness. Ensemble methods leverage the strengths of multiple models to achieve better results than individual models.
3. Explainable AI (XAI) Techniques: Implementing XAI methods would provide insights into the rationale behind the model's predictions. Understanding how the model arrives at its conclusions would foster trust and transparency in its application within Islamic boarding schools. XAI techniques can help educators and administrators understand which factors the model prioritizes when making predictions.

By continuing to develop and refine FFNN models for predicting student graduation outcomes, Islamic boarding schools can benefit from a more objective, efficient, and scalable approach to student evaluation, ultimately contributing to informed decision-making and improved student success rates.

V. Conclusions

This research addressed the predictive modeling of graduation outcomes among prospective students at Nuur Ar Radhiyyah Islamic boarding school using Feedforward Neural Networks (FFNNs). The methodology encompassed data collection, processing, and model configuration, culminating in a comprehensive examination of model performance.

Through a meticulous analysis of 480 prospective student evaluations encompassing crucial features and target classes, we gained a deeper understanding of the dataset. The Orange Data Mining application played a pivotal role in data processing, offering an efficient approach to handle the dataset. The model configuration involved the creation of 12 distinct models, each with varying activation functions, hidden layers, and neuron counts. The use of 10-fold cross-validation provided a robust framework for evaluating model performance.

In the result and discussion section, the performance of these models was rigorously assessed. For models with 2 neurons per hidden layer, it was evident that the choice of activation function had a notable impact. The Sigmoid-based models exhibited stability regardless of the neuron count in their hidden layers. Conversely, the ReLU-based models showcased sensitivity to changes in neuron count, with notable performance improvements as neuron counts increased. This highlighted the need for careful architecture selection, particularly when utilizing ReLU activation functions.

In summary, this research sheds light on the intricate relationship between FFNN configurations and predictive accuracy. It underscores the significance of selecting an appropriate activation function and optimizing the architecture by considering the number of neurons per hidden layer. These findings offer valuable insights for educational institutions seeking to employ predictive modeling for graduation outcomes and lay the foundation for further exploration in this field. For comparison purposes, researchers interested in further developing this study can access the dataset used by the author on Kaggle.com [34].

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