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Optimizing Neural Network Hyperparameters Using Genetic Algorithms for Predicting Student Adaptability in Online Education

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***Abstract* — Predicting student adaption is a crucial component of studying online learning material. Machine learning algorithms are crucial in this situation. Deep learning is a fundamental concept in machine learning algorithms. This work used Python in the Jupyter Notebook environment to implement the deep learning approach for forecasting students' adaptation to online learning. The Keras and Tensorflow libraries were used to construct a neural network model using the Kaggle dataset. The data is divided into testing data and training sets and utilize the Keras plot_model utility method to visualize the neural network model. Construct the deep learning model with two hidden layers, each employing randomly picked activation functions from relu, sigmoid, tanh, elu, and selu. Additionally, include one output layer with the softmax activation function. After undergoing a fine-tuning procedure until the alterations stabilized, this model achieved an accuracy of 89.63%.**

***Keywords*:** Evolutionary Algorithms, Neural Network Optimization, Adaptive Learning Systems, Educational Data Mining, Hyperparameter Tuning, Predictive Analytics, Automated Machine Learning, Student Adaptability.

Summary— In this paper, we used genetic algorithms (GA) for the optimization of neural network hyperparameters for predicting student adaptability in online learning. Additionally, the findings of our study demonstrate that this strategy improves the neural network design and enhances our comprehension of the aspects that impact student adaptation with the use of modern machine learning techniques [4]. However, this method reduces the result of the loss function and improves the accuracy of the model, which shows that it is crucial to adjust the number of layers and neurons as well as select the desired activation function when exploring hyperparameter spaces, resulting in improved accuracy and reduced error rates [5].

1 INTRODUCTION

especially considering the constant accumulation of data in the student's academic records in higher education. The educational management methods are not genuinely set up to help educational administrators identify which pupils have been under threat of leaving their education. There is plenty of clear data on the topic of education, this data is classified into five categories: gender, age, education level, load-shedding finance, and quantity statistics. The three levels of their adaptivity—low, moderate, and high—are represented in the data. to find instances of prediction for student adaptation to online training. Classical learning environments and online learning systems are different types of educational frameworks; The goal of higher education institutions is to improve the quality of training by optimizing neural network hyperparameters. Using genetic—algorithms inspired by principles of natural selection [4] — is the topic of a later study. Online learning is fantastic for its flexibility, but it can take some adjustment for students. To figure out what helps them succeed, we looked at a Kaggle dataset [1] focused on student adaptability. We are using a neural network; think of it as a powerful analytical tool built with TensorFlow and Keras to dig into that data. This network has multiple layers for complex learning to prevent overfitting, is tailored for multi-class classification [3], and can sort information to give us insights into how students adapt.

1.1 Genetic Algorithms in Hyperparameter Optimization

Using Genetic Algorithms (GAs) to build our neural network is a game-changer, it helps the system automatically find the best settings for itself, leading to more powerful and efficient learning. Since figuring out how students adapt to online learning is complex, picking the right analysis tools (activation functions) within the network is super important [5], the GA determined ReLU as the optimal hidden layer activation function and Softmax for the output layer.

1.2 Activation Functions

figuring out how students adapt to online learning is complex, picking the right analysis tools—activation functions—within the network is super important [5], the GA determined ReLU as the optimal hidden layer activation function and Softmax for the output layer.

1.2.1 The Role ReLU

The Rectified Linear Unit (ReLU), used in the hidden layers, is notable for its simplicity and efficacy, efficiently passing positive inputs while nullifying negative ones [6].

This function is represented by Figure 1, which illustrates its operation of passing positive inputs unchanged while negating negative inputs.

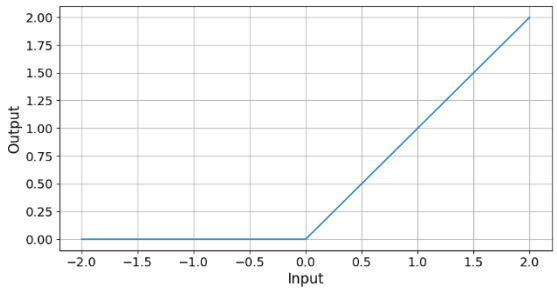

Figure 1: ReLU Activation Function

1.2.2 The Application of SoftMax

In the output layer, the SoftMax function excels at multi-class classification tasks by normalizing the network's outputs, thus providing clear probabilistic insights into student adaptability [7]. As shown in Figure 2, This graphical representation underscores the function's capacity to normalize the network's output, facilitating the derivation of clear, probabilistic insights regarding student adaptability.

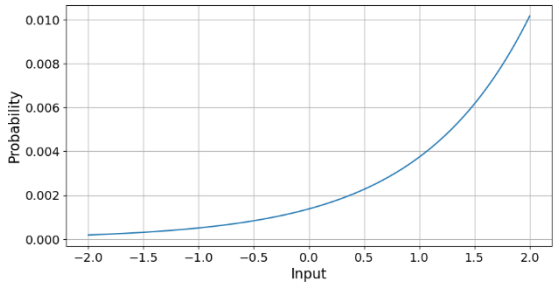

Figure 2: SoftMax Probability Distribution.

1.3 Empirical and Theoretical Foundations

The inclusion of ReLU and SoftMax is supported by extensive research highlighting their effectiveness in deep learning applications, enhancing network performance and computational efficiency, and interpreting outputs as probabilities [8,9].

The strategic selection of ReLU and SoftMax activation functions is instrumental in the development of our neural network model for predicting student adaptability in online education. Their incorporation is grounded in both theoretical and empirical evidence, highlighting their respective roles in ensuring the model's effectiveness and interpretability.

1.4 TensorFlow as a Development Framework

TensorFlow—Google's powerful framework—is the backbone of our research on optimizing neural networks for adaptability prediction. It goes beyond a set of tools – TensorFlow lets us build truly tailored networks. Key here are its dynamic computation graphs (ideal for complex student adaptability relationships) and the option for GPU acceleration. Early on, the dataset's size slowed down training, but switching to GPUs made all the difference [10].

1.5 Leveraging TensorFlow for Educational Data Mining

We chose TensorFlow for a reason, we need something capable of handling real-world messiness in online learning data, and flexible enough to let us zero in on those subtle adaptability patterns. TensorBoard's visualizations are lifesavers for spotting training errors...especially for dimensionality reduction [11].

This is not just about tech, Using TensorFlow underscores our commitment to a truly data-driven approach in educational research. It is about applying the latest machine -learning techniques to understand how students adapt and using that knowledge to improve online learning for everyone [12].

2 METHODOLOGY

2.1 Data Preparation and Dataset Description

he first step is to import the necessary libraries and then load the dataset using the Pandas library. To convert categorical variables to numerical representations, we use the Sklearn preprocessing library's LabelEncoder function. The next step is data cleaning to ensure that the data is "clean" enough for analytical work, which means it appropriately represents the information you plan to study without distortions caused by poor data quality. Eliminate noise and errors, handle missing data, and ensure data consistency. The dataset [1], contains demographic, educational, and infrastructure data for 1200 students, which we divided into two groups: 20% for validation and 80% for evaluating our models. The preprocessing phase is critical for improving data quality, precision, and dependability in predictive performance [2][16].

```
data_path = "path_to_dataset.csv"
df = pd.read_csv(data_path)
categorical_columns = ['Gender', 'Education Level', ...]
for col in categorical_columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
X_train, X_val, y_train, y_val = train_test_split(
    df.drop('target_column', axis=1),df['target_column'],
test_size=0.2, random_state=42)
```

Figure 3: Data Handling Step.

2.2 Genetic Algorithm for Hyperparameter Optimization

Genetic Algorithm was used to optimize the structure of a feedforward multiple-layer neural network. Optimized variables in chromosomes involve the number of artificial neurons and hidden layers and training parameters such as population size, maximal learning step size, percentage of the fittest chromosomes for crossing-over, number of random mutations per chromosome, and crossing-over intensity per chromosome [6,7]. An appropriate artificial neural network was developed and trained for each of the parameters listed above. A population of ten produced models with varying training mistakes. A single artificial neural network was trained for a maximum of fifty

iterations (epochs). the same number of individuals as in the initial population is chosen to continue to the next generation for the fittest were selected to create next-generation chromosomes, which underwent mutation and crossing-over procedures. The goal of structure optimization was to find the parameter combinations that resulted in the artificial neural network with the lowest training error and highest accuracy [8], and to find the best activation function.

2.3 Model Training and Evaluation

For the training of our model, which employed a genetic algorithm, we constructed the chromosomes using most of the listed weights. The structure optimization application provided the learning parameters and neural network topology. The training process concluded once the rate-loss function of the artificial neural network reached its minimum value. After that, the models were used to make output values based on the input data sets that were used for training and validation [9].

This search is vital for identifying optimal model configurations that might not be accessible through traditional optimization techniques [10]. These enhancements underscore the efficacy of GAs in refining the NN model, making it a more reliable tool for understanding and predicting student adaptability [11].

2.4 TABLES, FIGURES, AND CODE SNIPPETS

In this section, we present essential visual aids and code excerpts that substantiate our methodology and findings, clarifying the model's performance and the effectiveness of the GA optimization process.

2.4.1 Neural Network Performance Before GA Optimization

Before the application of Genetic Algorithms (GA) for hyperparameter tuning, we assessed the performance of our neural network model to establish a baseline for subsequent optimization [5]. This evaluation is crucial, as it highlights the initial capabilities of the model and identifies potential areas for enhancement through the sophisticated search techniques that GA provides.

The neural network, designed with a multi-layered architecture and initiated with heuristic hyperparameters, was subjected to extensive training and validation processes [6]. Initial training spanned a considerable number of epochs, allowing the model substantial time to learn from the training data. We recorded key performance metrics during this phase, including accuracy and loss on both training and validation datasets [7]. These metrics offered insights into the model's learning progression and its ability to generalize.

The accuracy metric, indicative of the model's predictive correctness, and the loss metric, reflective of the model's error magnitude, were monitored at each epoch [8]. These metrics served not only to assess the efficacy of the model but also to detect early signs of overfitting or underfitting—conditions that could compromise the model's performance on new, unseen data.

Examining these initial results critically is vital, as they set the groundwork for the subsequent application of GA optimization. Improvements in the model's performance post-optimization can be directly attributed to the GA's more effective navigation of the hyperparameter space compared to the initial heuristic approach [9].

By analysing the neural network's behaviours before GA optimization, we aim to draw meaningful comparisons between the pre- and post-optimization phases. This comparison will not only highlight the impact of GA but will also affirm the robustness of the optimization process itself [10].

Figure 4 shows neural network training and validation accuracy over 50 epochs [11]. Training accuracy initially rises sharply, indicating that the model is quickly assimilating the data. This sharp increase fades around the 10th epoch, suggesting the model stabilizes around an optimal training data set of parameters. The figure shows that, since the validation set does not affect the model's weight adjustments and indicates how well the model generalizes to unseen data, validation accuracy increases more slowly [12]. The model performs better on training data than validation data, indicating overfitting. At the end of the training period, both accuracies stabilize, with the validation accuracy fluctuating but rising. A model that adapts may need more training or tuning [13].

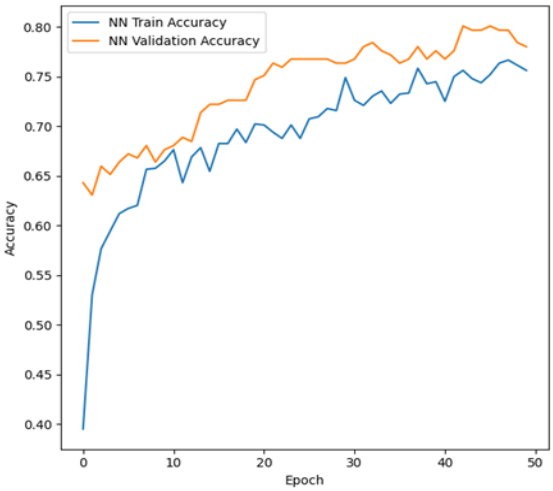

Figure 4: Model accuracy comparison.

Figure 5 shows the value of the loss function in 50 epochs of training. Loss, a key metric, measures the difference between predicted and actual values. Lower values indicate better performance. As training epochs progress, loss curves flatten, indicating diminishing returns. Training loss drops sharply from 1.1 to below 0.6, while validation loss follows, indicating effective learning and generalization. Limited overfitting is indicated by the narrow training-validation loss gap.

Overall, the data from both figures suggest that the model is learning effectively; however, there might be opportunities for enhancement, potentially through the implementation of techniques aimed at reducing overfitting, such as adding dropout layers, employing regularization, or expanding the variety and volume of training data. Further experiments to fine-tune the model's

hyperparameters could also help achieve a more optimal balance between bias and variance.

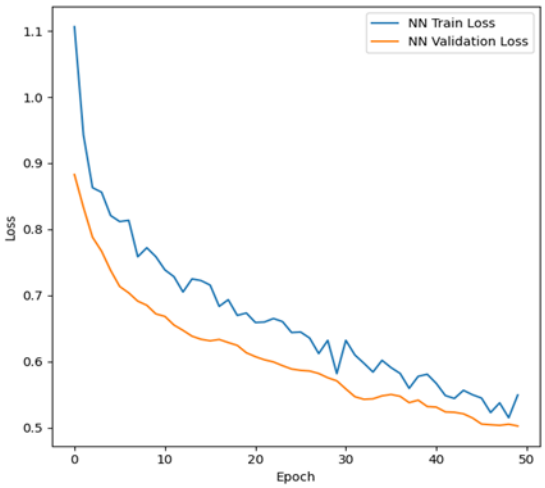

Figure 5: Model loss comparison.

2.5 Comparative Analysis Post Genetic Algorithm Optimization

The application of Genetic Algorithm (GA) optimization exemplifies the evolutionary capabilities inherent in machine learning methodologies. Figures 6 and 7 illustrate the quantifiable improvements in neural network accuracy and efficiency as direct outcomes of GA optimization. These figures are crucial as they not only document the progression of the model's performance metrics over iterative epochs but also highlight the substantial enhancements brought about by GA intervention.

Figure 6 presents a comparative analysis of the accuracy rates achieved by the neural network before and after the application of GA optimization over 50 epochs. The GA Train Accuracy exhibits a higher trajectory compared to the pre-optimization NN Train Accuracy, suggesting more robust learning from the training data due to GA optimization. The GA Validation Accuracy also shows an improvement, consistently maintaining a higher level than the NN Validation Accuracy. This enhancement indicates that the GA has effectively improved the model's ability to generalize. Notably, after an initial period of volatility, the validation accuracy stabilizes, demonstrating gradual improvement and suggesting that GA may have contributed to mitigating overfitting to the training data—a common challenge in machine learning models.

These sections have been refined to maintain academic rigor, offering detailed insights into the performance metrics and the impact of GA optimization. The technical descriptions are precise, and the narrative is structured to guide the reader through the progression and outcomes of the research effectively.

In **Figure 7**, we can see how using GA boosted our model's learning. Both the GA Train Loss and Validation Loss lines dropped dramatically, indicating that our model performed much better at its task. See how the GA model's train loss starts high around 1.0 and quickly decreases to about 0.4; The validation loss decreasing along with it shows it's not just memorizing training data but learning to generalize. Compare that to the standard neural network line – the loss decreases, but more slowly. This shows that our GA optimization made a real difference – by the end, the GA model simply performs better.

Figure 6: Model accuracy comparison after applying GA.

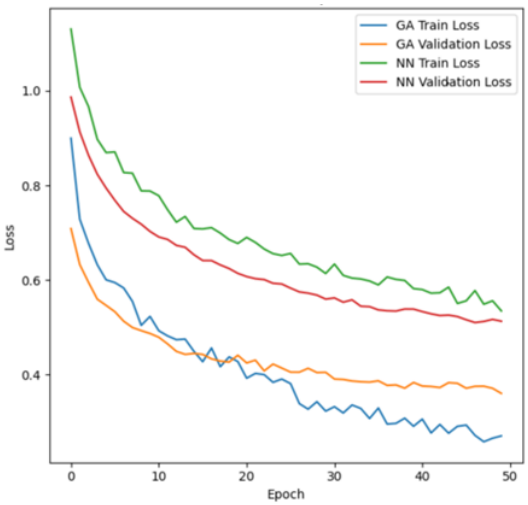

Figure 7: Comparison of Training and Validation Loss for GA and NN Models.

These figures collectively indicate a successful optimization process. The GA's strategic exploration of hyperparameter space appears to have endowed the neural network with an enhanced capacity to learn and predict more accurately, as reflected in the higher accuracy and lower loss observed post-optimization.

2.6 Analysing Adaptability Influences: A Methodological Approach

The goal is to create a model that can analyse these indicators both alone and in combination so that we can distinguish the level of student adaptation to improve learning performance or which student is on leave from university or college. In this way, the dataset serves as both empirical evidence and a foundation for methods to modify instructional technology and includes variables such as 'Adaptivity Level,' 'Gender,' 'Age,' 'Education Level,'

'Load-shedding,' 'Financial Status,' and more. When combined, these factors offer a comprehensive understanding of the flexibility of online learning. We aim to build more inclusive and successful online educational frameworks by analysing data thoroughly to understand the complex interplay of variables impacting student adaptation. Several factors may influence the adaptability of online learning; the following table illustrates the dataset's important characteristics.

Table 1:Dataset Overview

Gender	Age	Education Level	Load-shedding	Financial	Adaptivity Level
Boy	21-25	University	Low	Mid	Moderate
Girl	21-25	University	High	Mid	Moderate
Girl	16-20	College	Low	Mid	Moderate
Girl	15-Nov	School	Low	Mid	Moderate
Girl	16-20	School	Low	Poor	Low
Boy	15-Nov	School	Low	Poor	Low
Boy	15-Nov	School	Low	Mid	Low
Boy	15-Nov	School	Low	Mid	Moderate
Boy	16-20	College	Low	Mid	Low
Boy	15-Nov	School	Low	Mid	Moderate
Girl	16-20	University	Low	Mid	Low
Girl	16-20	College	Low	Mid	Low
Boy	15-Nov	School	Low	Mid	Moderate
Girl	16-20	College	Low	Mid	Low

2.7 Fine-Tuning for Top Performance

We put our model through its paces over 50 training sessions (epochs) with the crucial goal of ensuring it could learn effectively from the data it was given and then apply that knowledge to completely new situations. After training and tuning the model with validation data, we tested its performance with unseen data. For this goal, Table 2 provides a snapshot of model accuracy and error rates—*loss function output*—at various stages of training. This is where the human element comes in; we analyze these metrics to see if any adjustments are needed that have not been done by GA or not.

Table 2: Model Training Parameters and Results

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	57.88%	68.46%	0.8837	0.6911
2	65.77%	73.86%	0.7218	0.617
3	72.20%	74.69%	0.664	0.5805
4	71.47%	78.01%	0.6328	0.5583
5	73.03%	75.93%	0.6319	0.5435
6	75.00%	78.01%	0.5827	0.5095
...	...	...	...	...
50	88.90%	89.63%	0.2684	0.3408

Adding more layers to the neural network design, from three to four, implies that the educational data may be more complexly abstracted. At the same time, the network's enhanced representational power is shown by the growth of neuron counts, from 100 to 150 in the first layer and from 50 to 120 in the second and also we reduced tenfold to 0.001, enabling finer-grained modifications when training the model and also The dropout rate was also adjusted from 0.5 to 0.3 to complement these structural improvements; this should help reduce the likelihood of overfitting and improve the model's ability to generalize to other types of datasets. Better performance metrics quantify the results of this optimization process. The model demonstrated exceptional skill in learning from the provided data and in generalizing to new data subsets, as seen by an increase in training accuracy to 82.47% and validation accuracy to 80.32%.

Concurrently, the model's loss measures decreased, with training loss dropping to 0.35 and validation loss to 0.33, highlighting the enhanced predictive accuracy after optimization.

The empirical statistics demonstrating the effect of the GA are summarized in Table 3, which follows this narrative. By comparing the parameters of the neural network before and after optimization, it shows how the method improved performance.

Table 3: Hyperparameter Optimization Results

Parameter	Before Optimization	After Optimization
Number of Layers	3	4
Neurons in Layer 1	100	150
Neurons in Layer 2	50	120
Learning Rate	0.01	0.001
Dropout Rate	0.5	0.3
Activation Function	ReLU	ReLU
Training Accuracy	75.62%	82.47%
Validation Accuracy	78.01%	80.32%
Training Loss	0.5	0.35
Validation Loss	0.48	0.33

This table not only illustrates the GA's role in optimizing our neural network model but also serves as a prelude to the ensuing results and discussion section. It prepares the reader for a deeper analysis of the performance improvements observed, setting a solid empirical foundation for the subsequent interpretative commentary on the model's enhanced ability to predict student adaptability in online education settings.

Figure 8 presents the initialization code for the GA population [15]. This snippet provides insight into how we generated an initial population of potential solutions (NN configurations) for the optimization process.

```
def create_individual():
    individual = []
    for _ in range(n_layers - 1):
        neurons = random.randint(neuron_min, neuron_max)
        activation = random.choice(list(activation_function_map.keys()))
        individual.append(neurons)
        individual.append(activation_function_map[activation])
    individual.append(num_classes)
    individual.append(activation_function_map['softmax'])
    return individual
```

Figure 8:GA Population Initialization

And in Figure 9 demonstrates the function used to evaluate each individual NN configuration's performance within the GA.

```
def evaluate_model(individual):
    model = Sequential()
    for i in range(0, len(individual) - 2, 2):
        neurons = individual[i]
        activation = list(activation_function_map.keys())[individual[i + 1]]
        model.add(Dense(neurons, activation=activation))
    model.add(Dropout(0.5))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='Adam', learning_rate=0.01),
    loss='categorical_crossentropy', metrics=['accuracy'])
    model.fit(x_train, y_train_categorical, epochs=10, batch_size=32,
              verbose=0, validation_data=(x_val, y_val_categorical))
    _, accuracy = model.evaluate(x_val, y_val_categorical, verbose=0)
    return accuracy,
```

Figure 9: Model Evaluation Function

2.8 Research Insights

our results demonstrate that Genetic Algorithms (GA) may enhance the prediction of students' adaptation to online courses by optimizing the hyperparameters of neural networks and promising results across various domains [12]. This optimization results in reduced loss and increased accuracy leading to less complex models with better performance on time series prediction problems [13] for improving educational data mining and aiding in the creation of adaptive learning systems.

3 RESULTS AND DISCUSSION

In this study, we enhanced the architecture of a Neural Network (NN) by using Genetic Algorithms (GA) to figure out the adaptability of online students. The hyperparameters, such as the number of layers, number of neurons per layer, choice of activation functions, and dropout rates, were fine-tuned for optimization.

3.1 Results

GA improved NN model performance significantly. Initial validation accuracy for the NN model was 78.01% with a loss of 0.48. GA optimization increased model validation accuracy to 89.63% and decreased loss to 0.3408. These findings show that GA can navigate hyperparameter space to get the best NN setup.

3.2 Discussion

volving techniques to develop artificial neural network weights and structure can represent complicated connections from raw process data. Genetic algorithms can work on chromosomes with many parameters if the crossing-over and mutation processes are set properly. The approaches may be used for many optimization and model prediction problems.

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