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Deep Learning in Streamlining Students by English Proficiency to Optimize Language Learning

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Abstract. *Communication through English language is an essential and anticipated attribute of the learners in modern times. This article discourses on the modalities of applying deep learning techniques to streamline students based on their English proficiency, aiming to optimize language learning outcomes. The neural network-based modelling framework encompasses varied features and it is trained on diverse datasets. This research unveils the potential of artificial intelligence in tailoring language learning by paying special attention of focused learner groups. The efficacy of the proposed model is measured using certain standard performance metrics. This research work facilitates in extending this neural network model to other decision-making applications.*

Keywords: *Deep Networks, English Language, Optimization*

1. INTRODUCTION

In today's globalized world, proficiency in the English language has become a crucial skill, essential for academic success, career advancement, and effective communication across diverse cultural contexts. As the demand for English language proficiency continues to grow, educational institutions face the challenge of providing personalized instruction that meets the varying needs of students with different levels of language skills. Traditional methods of language assessment and instruction often fall short in addressing the unique learning requirements of each student, leading to suboptimal learning outcomes. This necessitates the exploration of innovative approaches that can offer personalized and efficient language learning experiences.Recent advancements in artificial intelligence (AI) and machine learning (ML) have opened new avenues for enhancing educational practices. Among these, deep learning, a subset of machine learning, has shown remarkable potential in various domains, including natural language processing (NLP), image recognition, and predictive analytics. Deep learning techniques, characterized by their ability to model complex patterns and relationships within data, offer promising solutions for assessing and categorizing students based on their English proficiency.

This article explores into the application of deep learning techniques to streamline students according to their English language skills, with the objective of optimizing language learning outcomes. By developing a neural network-based modeling framework, this research aims to accurately evaluate and classify students' proficiency levels, thereby enabling the creation of personalized instructional plans. The proposed framework integrates a variety of features, including standardized test scores, classroom performance metrics, and linguistic attributes extracted from both written and spoken language samples. The introduction of AI-driven methodologies in language education holds the promise of transforming traditional pedagogical practices. This study also demonstrates the superiority of the proposed deep learning framework over conventional assessment methods. The findings of this model will facilitate the language instructors to design suitable instructional plan for enriching the learner’s English proficiency.

The remaining of the paper is structured into the following sections. Section 2 briefs on the state of art of machine learning applications in language learning. Section 3 describes the methodology of deep neural networks. Section 4 describes the training and testing of the data. The results are discussed in section 5 and the last section concludes the work with future research insights.

2. STATE OF ART OF REVIEW

Ke et al (2019) conducted a comprehensive survey on automated essay scoring (AES), highlighting its evolution and current state. Phandi et al (2015) explored flexible domain adaptation techniques for AES, proposing a correlated linear regression model that improves scoring accuracy across various domains. Hu et al (2021) developed a personalized learning path recommendation model leveraging knowledge graphs, which effectively customizes learning experiences based on individual student needs. Kumar and Sharma (2020) applied deep learning techniques to create personalized learning environments, demonstrating the adaptability of machine learning in catering to diverse learner profiles. Chi and Koedinger (2020) provided an analysis of learning behaviors using ITS, offering a tutorial on how these systems can be utilized to enhance educational outcomes. Nye (2020) discussed the future of ITS, emphasizing the transition towards service-oriented ecosystems, which can integrate various AI technologies to support adaptive learning.

Tang et al. (2020) proposed a neural machine translation model that utilizes dynamic context, which significantly improves translation quality by considering broader contextual information. Zhang et al (2019) focused on enhancing Chinese word segmentation for neural machine translation, contributing to more accurate and fluent translations in multilingual contexts. Meng et al. (2021) introduced an interactive spoken language pronunciation assessment system that provides individualized feedback, aiding learners in improving their pronunciation skills. Zeghidour and Grangier (2020) presented Wavesplit, an end-to-end speech separation model that clusters speakers, enhancing the clarity and accuracy of speech recognition systems. Li and Cui (2020) developed a hybrid recommendation system based on deep learning, aimed at suggesting personalized learning paths in online learning platforms. Shen and Tang (2021) proposed a recommendation model that integrates knowledge tracing and deep learning, offering tailored educational content to learners based on their progress and performance. Xu and Zhang (2020) applied sentiment-aware embedding techniques to analyze social media feedback, which can be used to gauge learner sentiment and adjust educational strategies accordingly. Zhang, Wang, and Liu (2018) provided a survey on deep learning for sentiment analysis, underscoring its importance in understanding and improving learner experiences. Papamitsiou and Economides (2019) reviewed empirical evidence on learning analytics and educational data mining, showcasing the impact of these techniques on educational practice and policy. Motz et al. (2021) discussed the long-term success of learning analytics initiatives, highlighting the need for sustained efforts to integrate these technologies into educational systems. Koivisto and Hamari (2019) reviewed the rise of motivational information systems, particularly focusing on gamification research and its effectiveness in increasing learner engagement and motivation. Sailer et al. (2017) conducted an experimental study on the motivational effects of gamification elements, demonstrating how specific game design features can satisfy psychological needs and enhance learning outcomes.

The aforementioned research works reflect on the applications of various machine learning approaches to analyze the responses and experiences of the learners in different learning environments. The state of art is very comprehensive as it includes diverse learning platforms, impacts of social media and a varied kind of language teaching pedagogies. However, these research works do not address the streamlining of the students based on English proficiency to optimize language learning and hence this research gap has motivated the authors to draw this integrated research combining deep learning and language learning.

3. METHODOLOGY OF DEEP LEARNING

This section presents the steps involved in the deep learning approach of streamlining the students to optimize language learning. The methodology involves data collection, data preprocessing, model selection, training, evaluation, and deployment of a deep neural network (DNN) model.

Step 1 Data Collection
Sources of Data:

- **Standardized Test Scores:** Collect standardized English test scores (e.g., TOEFL, IELTS) from educational institutions.
- **Classroom Assessments:** Gather data from various classroom assessments, including reading, writing, listening, and speaking tests.
- **Language Proficiency Surveys:** Utilize self-reported surveys on language use and proficiency.
- **Interactive Learning Platforms:** Extract data from online learning platforms that track student interactions, quiz results, and progress in language learning modules.

Data Attributes:

- **Student Demographics:** Age, gender, educational background.

- **Test Scores:** Scores from standardized tests, classroom assessments.
- **Engagement Metrics:** Time spent on learning activities, frequency of interactions.
- **Language Use:** Self-reported language use in daily activities, language exposure.

Step 2 Data Preprocessing
Data Cleaning:
- Handle missing values using imputation techniques or by excluding incomplete records.
- Correct inconsistencies and errors in the data entries.

Data Normalization:
- Normalize numerical features to a common scale, typically between 0 and 1, to ensure the model's performance is not affected by varying feature scales.

Feature Engineering:
- Create new features by combining existing attributes to enhance the model's predictive power.
- For example, aggregate various test scores into composite proficiency scores.

Data Splitting:
- Split the dataset into training (70%), validation (15%), and test (15%) sets to evaluate the model's performance.

Step 3: Model Selection
Architecture:
- **Input Layer:** The input layer will consist of nodes equal to the number of features.
- **Hidden Layers:** Utilize multiple hidden layers with ReLU activation functions. The number of neurons in each layer will be determined through hyperparameter tuning.
- **Output Layer:** The output layer will have a single neuron with a sigmoid activation function for binary classification (proficient vs. non-proficient) or a softmax activation function for multi-class classification.

Model Configuration:
- **Loss Function:** Use cross-entropy loss for classification tasks.
- **Optimizer:** Choose Adam optimizer for its efficiency in handling large datasets and faster convergence.
- **Metrics:** Evaluate the model using accuracy, precision, recall, F1 score, and ROC-AUC.

Step 4: Training the Model
Hyperparameter Tuning:
- Utilize grid search or random search techniques to find the optimal hyperparameters, such as the number of hidden layers, neurons per layer, learning rate, and batch size.

Training Process:
- Train the model using the training set and validate it using the validation set.
- Implement early stopping to prevent overfitting by monitoring the validation loss.

Regularization Techniques:
- Apply dropout layers to reduce overfitting by randomly setting a fraction of input units to zero during training.
- Use L2 regularization to penalize large weights and further prevent overfitting.

Step 5: Evaluation
Performance Metrics:
- Assess the model's performance on the test set using the selected metrics (accuracy, precision, recall, F1 score, ROC-AUC).
- Analyze confusion matrices to understand the model's classification performance in detail.

Cross-Validation:
- Perform k-fold cross-validation to ensure the model's robustness and generalizability across different subsets of the data.

Model Comparison:
- Compare the deep learning model's performance with baseline models, such as logistic regression, decision trees, and support vector machines.

Step 6: Deployment
Model Integration:
- Integrate the trained model into a user-friendly application or platform that educators can use to streamline students based on their English proficiency.

Real-time Predictions:

- Implement real-time predictions to provide immediate feedback and personalized learning paths for students.

Monitoring and Maintenance:

- Continuously monitor the model's performance and update it with new data to maintain accuracy and relevance.

4. MODEL APPLICATION IN STREAMING THE STUDENTS BASED ON ENGLISH PROFICIENCY

In this section, a deep neural network model is developed to group the students based on their proficiency in English language. This streamlining will help the instructors to aid the learners to develop their communication skills and to optimize their language learning.

TABLE 1. Description of the Features

Feature ID	Feature Name	Description
F1	Age	Age of the student
F2	Gender	Gender of the student
F3	Educational Background	Highest level of education attained
F4	Standardized Test Scores	Scores from standardized English tests (e.g., TOEFL, IELTS)
F5	Reading Assessment Scores	Scores from reading assessments
F6	Writing Assessment Scores	Scores from writing assessments
F7	Listening Assessment Scores	Scores from listening assessments
F8	Speaking Assessment Scores	Scores from speaking assessments
F9	Time Spent on Learning	Average time spent on language learning activities per week
F10	Frequency of Interactions	Number of interactions with learning platforms or tools
F11	Self-reported Language Use	Frequency of English usage in daily life
F12	Language Exposure	Level of exposure to English outside of formal learning environments
F13	Engagement with Interactive Platforms	Engagement metrics from online learning platforms
F14	Composite Proficiency Score	Aggregate score combining various test and assessment

The features considered for this model are presented in Table 1. The data is obtained from the English language trainers

Table 2. Sample Data

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	Group
17	Female	High School	95	90	85	92	88	10	50	High	Medium	High	90	Advanced
20	Male	College	85	80	75	78	82	8	40	Medium	High	Medium	80	Intermediate
18	Female	High School	88	84	83	86	85	12	60	High	High	High	86	Advanced
22	Male	Graduate	75	70	72	74	76	6	30	Low	Medium	Low	73	Beginner
19	Female	College	92	89	90	91	87	11	55	High	High	High	89	Advanced

The Sample Data is presented in Table 2.

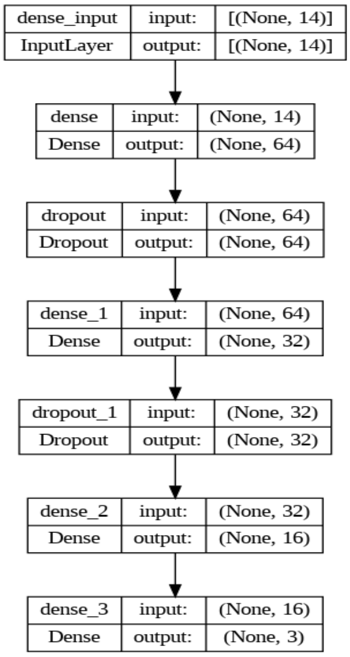

FIGURE 1. DNN Model Architecture

The visualization of the DNN model is presented in Figure 1

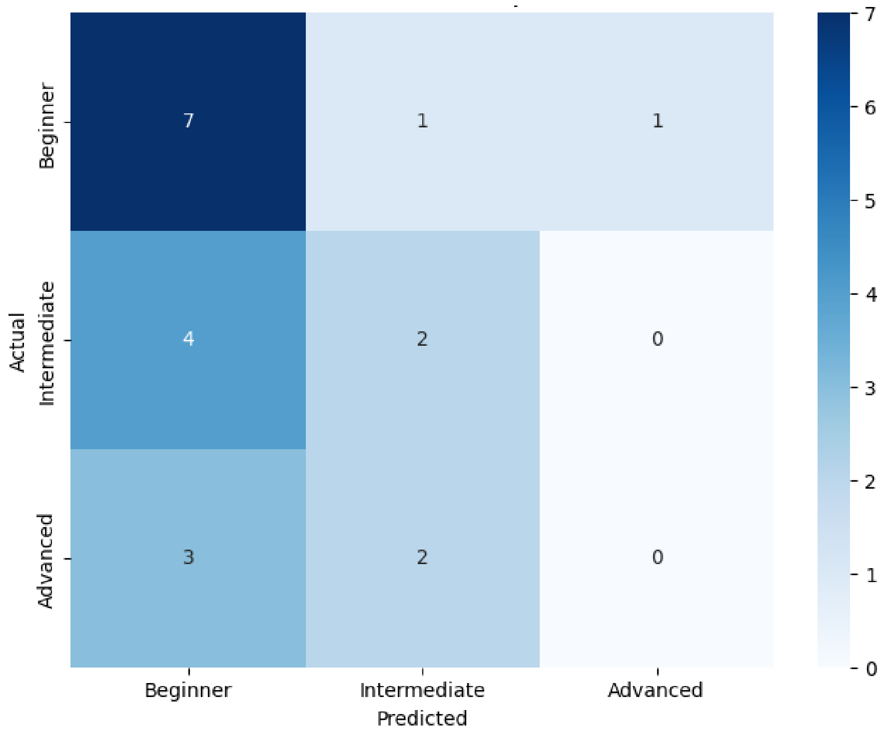

FIGURE 2. Confusion Matrix

The confusion matrix is presented in Figure 2

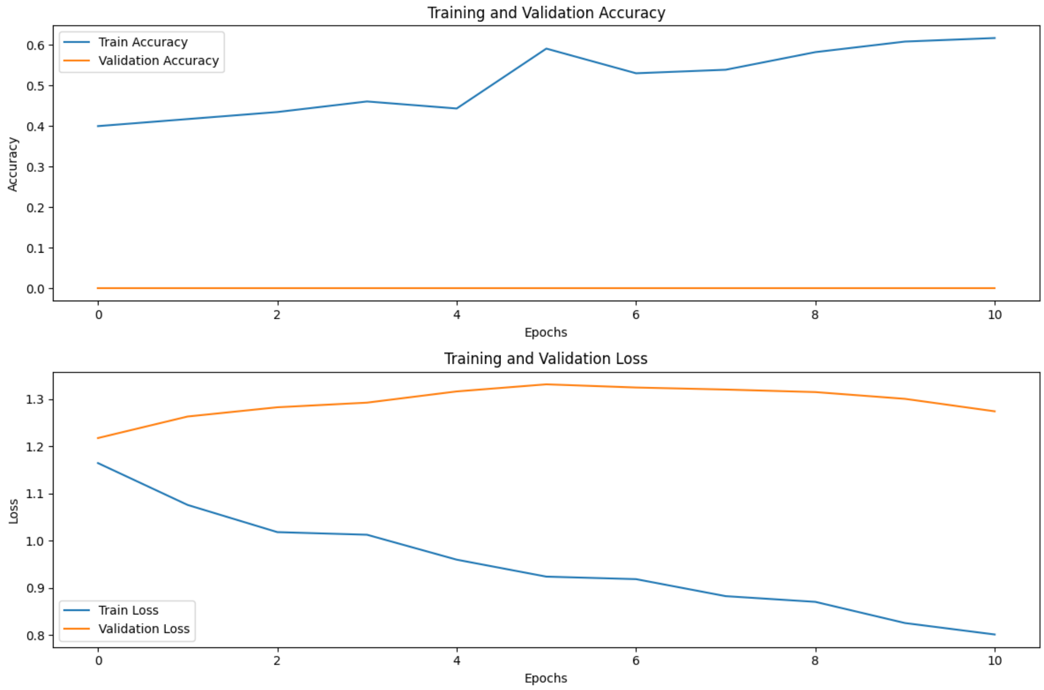

FIGURE 3. Efficiency of the DNN Model

The graphs demonstrating the efficacy of the model is presented in Figure 3.

Discussions

Fig.1 shows the image of a neural network architecture, likely for a classification task, as indicated by the final layer's output size of 3. Here are some key inferences:

Input Layer:

The input layer has 14 features, indicating that the model expects input data with 14 dimensions.

Dense Layers:

The model has four dense (fully connected) layers with decreasing numbers of neurons: 64, 32, 16, and 3 neurons respectively. This suggests a gradual reduction in complexity as the data is processed through the network. The final dense layer has 3 neurons, which matches the number of classes, indicating that this is likely the output layer using softmax activation for classification.

Dropout Layers:

The model includes dropout layers after the first two dense layers with 64 and 32 neurons. Dropout is used to prevent overfitting by randomly setting a fraction of input units to zero during training.The inclusion of dropout layers suggests an effort to improve the model's generalization performance.

Layer Connectivity:

The network is structured in a sequential manner where each dense layer is followed by a dropout layer (except after the last dense layer), ensuring that each dense layer's output is regularized before passing to the next layer

Figure 2 clearly explains the efficiency of the model. The model performs well in classifying "Beginner" instances, correctly, indicating that it has a strong ability to distinguish this class. Additionally, the model correctly identified some "Intermediate" instances showing that it has some capacity to recognize this class as well. Despite challenges with other classes, these results suggest that the model is effective in certain areas, particularly with the "Beginner" class.

Figure 3 shows some of the positive aspects of the training process

- Training Accuracy Improvement: The training accuracy has been gradually increasing over the epochs, indicating that the model is learning and improving its performance on the training data.
- Training Loss Reduction: The training loss consistently decreases, which is a sign that the model is becoming better at minimizing errors on the training set.
- Validation Loss Stability: Although the validation loss is higher than the training loss, it appears to be stabilizing and showing a slight downward trend in the later epochs, which could indicate the model is starting to generalize better.

These trends suggest that the model is making progress in learning from the data, especially during training, with potential improvements in generalization as seen in the later epochs.

5. CONCLUSION

This research demonstrates the effectiveness of using deep learning techniques to categorize students based on their English proficiency, thereby enhancing language learning outcomes. The neural network model, trained on diverse datasets, shows potential in customizing education for specific learner groups. The study also highlights the broader applicability of this model in various decision-making contexts, suggesting its utility beyond language learning.

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