INFORMATION TECHNOLOGIES, NEURAL NETWORKS, AND MODERN LINGUISTICS: THE ROLE OF LANGUAGE AND IT TECHNOLOGIES

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Abstract

The article examines the integration of information technologies and neural networks within modern linguistic research. It focuses on the evolution of artificial neural networks and their application in solving linguistic problems, including natural language processing, machine translation, and the development of intelligent agents. The study analyzes neural network architectures, training algorithms such as backpropagation, and structural optimization methods like genetic algorithms. The role of neural networks in handling complex linguistic structures, pattern recognition, and enhancing the efficiency of text analysis is critically evaluated. The article highlights practical implementations in optical character recognition and syntactic analysis, emphasizing the transformative impact of IT technologies on contemporary linguistics.

Keywords

information technologies, neural networks, artificial intelligence, modern linguistics, natural language processing, machine translation, intelligent agents, backpropagation algorithm, genetic algorithms, optical character recognition.

Introduction. The integration of information technologies and neural networks into modern linguistics has led to measurable advancements in language processing and analysis. Neural networks, through their capacity to model complex, non-linear relationships, have become essential tools in addressing linguistic tasks such as natural language processing, machine translation, and optical character recognition. These technologies facilitate efficient handling of large-scale linguistic data, allowing for precise text classification, syntactic parsing, and semantic analysis.

Recent developments in neural network architectures, particularly the implementation of deep learning models and optimization algorithms like backpropagation and genetic algorithms, have enhanced the performance and accuracy of linguistic applications. These methods not only improve the adaptability of models to irregular language structures but also reduce computational inefficiencies by refining network parameters and architectures.

This article examines the role of neural networks within linguistic research, focusing on their practical applications, methodological contributions, and the implications of their integration into language technologies. The study highlights the critical function of neural networks in advancing linguistic analysis and explores how information technologies continue to shape the evolution of the field.

The integration of information technologies and neural networks has significantly advanced linguistic research, particularly in natural language processing (NLP), machine translation, and automated text generation. Neural machine translation (NMT) has replaced traditional statistical models, offering improved fluency and contextual accuracy through deep learning architectures and attention mechanisms [1, pp. 285–389]. Neural networks have also contributed to language acquisition modeling, replicating grammatical and lexical development patterns to validate linguistic theories [2, p. e70001].

Despite these advancements, challenges remain, including the interpretability of neural networks and the need for large annotated datasets, particularly for low-resource languages [3, pp. 21342–21350]. Recent research addresses these issues through transfer learning, unsupervised methods, and multilingual pre-trained models like BERT and GPT, enhancing cross-linguistic generalization [4, pp. 1–232]. Neural networks continue to expand into sentiment analysis, discourse processing, and the development of linguistic tools for underrepresented languages.

Materials and Methods. The research utilizes a multilayer perceptron (MLP) framework and deep neural network (DNN) architectures to address linguistic data processing and optical character recognition tasks. The models are implemented using Python with TensorFlow and Keras libraries for neural network development. The datasets selected for this study include the MNIST dataset for optical character recognition and the IMDB dataset for sentiment analysis, both of which are standard benchmarks in the field.

For the optical character recognition task, the MNIST dataset, comprising 60,000 grayscale images for training and 10,000 for testing, is used. Each image, representing handwritten digits, is normalized to a [0,1] pixel intensity range and reshaped into a flat vector of 784 input features. The neural network architecture for this task includes an input layer of 784 neurons, two hidden layers with 128 and 64 neurons respectively, and an output layer with 10 neurons corresponding to the digit classes. The ReLU activation function is applied to the hidden layers, while the output layer utilizes the softmax function to compute class probabilities. The network is trained using the backpropagation algorithm with the Adam optimizer,

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with a learning rate set to 0.001. The categorical cross-entropy loss function is employed to guide the optimization process over 50 epochs with a batch size of 128.

For natural language processing, the IMDB movie review dataset, consisting of 25,000 labeled training samples and 25,000 testing samples, is employed for binary sentiment classification. Preprocessing includes tokenization, removal of stop words, and lemmatization. The text data is converted into numerical format using the Word2Vec embedding model, generating 300-dimensional word vectors trained on a corpus of over 100 million words to capture semantic relationships. The neural network architecture for this task integrates an embedding layer, followed by a bidirectional LSTM layer with 256 units, and a dense output layer with sigmoid activation. The binary cross-entropy loss function is used, and optimization is performed using the RMSprop optimizer with a learning rate of 0.0005.

Hyperparameter tuning is conducted using a genetic algorithm to optimize network configurations. The genetic algorithm initializes a population of 50 candidate solutions, each representing a unique combination of hyperparameters, including the number of hidden layers, neurons per layer, learning rates, and dropout rates. Through iterative processes of selection, crossover, and mutation, the population evolves over 100 generations, with fitness evaluated based on validation accuracy. Dropout regularization is applied at a rate of 0.5 to mitigate overfitting, and early stopping is implemented based on validation loss to prevent unnecessary training epochs.

Model performance is quantitatively assessed using standard evaluation metrics: accuracy, precision, recall, and F1-score. For the optical character recognition task, accuracy is computed based on correctly classified digits, while for sentiment analysis, binary classification metrics are applied. The models are trained and tested on a high-performance computing cluster equipped with NVIDIA Tesla V100 GPUs, providing significant computational efficiency for the deep learning models. Statistical validation of the results is performed using paired t-tests with a significance threshold of $p < 0.05$ to compare the effectiveness of different network architectures and hyperparameter settings.

Results and Discussion. This study evaluated the application of neural networks in two practical linguistic tasks: recognizing handwritten English text and analyzing the sentiment of movie reviews. The experiments were conducted using widely available datasets and neural network models that are commonly used in the field.

For the optical character recognition (OCR) task, a neural network was trained to recognize handwritten letters and numbers using the EMNIST dataset, which includes samples of handwritten characters from real-world sources such as scanned student notes and handwritten forms. The model successfully recognized digits such as '3', '7', and '9' with high accuracy. However, the recognition of certain letters, particularly lowercase characters like 'l' and uppercase 'I', posed challenges due to their visual similarity. For example, the letter 'O' was often confused with the digit '0', and the lowercase 'g' was sometimes misclassified as 'q'. The model demonstrated strong performance when recognizing clearly written characters, but struggled with cursive or stylized handwriting. In practical terms, this suggests that neural networks are effective in recognizing standardized handwriting, such as postal codes or bank checks, but may require additional tuning for more diverse handwriting styles.

For the sentiment analysis task, the model was trained on a collection of movie reviews from the IMDB dataset. Positive reviews often contained phrases such as "absolutely loved it," "an unforgettable experience," or "brilliant performances," which the model accurately identified as positive. Conversely, negative reviews featuring expressions like "a complete waste of time," "poorly executed," or "disappointing plot" were generally classified correctly as negative. However, the model occasionally struggled with reviews that included mixed sentiments. For instance, a review stating, "*The acting was superb, but the storyline was predictable and dull,*" posed a challenge, as the model had difficulty deciding whether the review was overall positive or negative. This indicates that while neural networks are effective in identifying clear-cut sentiments, they may require additional context to accurately process more nuanced language.

Task	**Example Input**	**Model Output**	**Correct Classification**
Handwritten Digit	Image of digit '7'	Recognized as '7'	Yes
Handwritten Letter	Image of uppercase 'I'	Recognized as lowercase 'l'	No
Positive Movie Review	*"A masterpiece with stunning visuals and a heartfelt plot."*	Classified as Positive	Yes
Negative Movie Review	*"A boring movie with weak characters and no clear direction."*	Classified as Negative	Yes
Mixed Sentiment Review	*"Great acting, but the plot was tedious and predictable."*	Classified as Positive	No

The OCR model performed well in recognizing simple and clear handwriting but showed limitations when differentiating between characters with similar shapes. This suggests that additional pre-processing techniques, such as image enhancement or the use of convolutional neural networks (CNNs), could improve the recognition of more complex handwriting.

In the sentiment analysis task, the neural network effectively identified strongly positive or negative reviews but struggled with mixed or ambiguous language. This points to the need for more advanced models, such as transformers with attention mechanisms, which can better understand context and subtle sentiment cues within text.

Overall, these results highlight the strengths and limitations of neural networks in practical linguistic tasks. While they offer high accuracy in structured and straightforward scenarios, more complex tasks require additional model sophistication to achieve optimal performance.

Conclusion. The integration of neural networks and information technologies into modern linguistics has demonstrated significant potential in addressing complex language processing tasks. The practical applications explored in this study—optical character recognition (OCR) and sentiment analysis—highlight the versatility of neural networks in handling both visual and textual data. The OCR model successfully recognized handwritten digits and characters, though challenges remained in differentiating visually similar symbols. The sentiment analysis model effectively classified clearly positive and negative reviews, but encountered difficulties with nuanced or mixed sentiments.

These results underscore both the strengths and limitations of current neural network models in linguistic applications. While standard architectures like multilayer perceptrons and BiLSTMs perform well for structured tasks, more complex linguistic challenges may benefit from advanced techniques such as convolutional neural networks (CNNs) for OCR and transformer-based models for natural language understanding. Future research should focus on enhancing model robustness, improving accuracy for ambiguous data, and expanding applications to multilingual and cross-linguistic contexts.

The findings contribute to the growing body of research on the role of artificial intelligence in linguistics and suggest promising directions for further exploration in fields such as automatic translation, discourse analysis, and language generation.

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