TECHNICAL SCIENCES

AUTOMATED EVALUATION OF ACOUSTIC QUALITY OF PREMISES USING DEEP LEARNING

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Abstract

This research is dedicated to the development and evaluation of a deep learning model for automated evaluation of acoustic quality of premises. The model was trained on a large dataset, which included various acoustic parameters, and showed high accuracy, sensitivity, specificity, and F1-score. However, some areas were identified where the model could be improved, particularly in assessing the acoustic quality of premises with a high level of noise. Despite these challenges, the research results confirm the potential of using deep learning in the field of acoustic design. This opens up new opportunities for further development and improvement of methods for automated evaluation of acoustic quality of premises, which may have important practical implications for this field.

Keywords: deep learning, acoustic quality of premises, automated evaluation, acoustic design, deep learning model, noise assessment

INTRODUCTION

The acoustic quality of premises plays an important role in the comfort and productivity of people who stay in them. It affects language understanding, music perception, and the overall comfort of users of the premises. However, the evaluation of acoustic quality of premises is a complex process, which traditionally requires significant effort and expert knowledge [1] .

Modern methods of evaluating the acoustic quality of premises include measuring various acoustic parameters, such as post-resonance time, speech clarity, and others. These methods can be labor-intensive and require special equipment and expert knowledge to interpret the results [2].

However, with the advent of deep learning, there is an opportunity to automate this process. Deep learning is a subfield of artificial intelligence that uses neural networks with many layers (so-called "deep" networks) to model complex relationships. It is already successfully applied in many fields, including acoustics.

METHODS

For processing these data, a deep learning model was developed. The model was based on convolutional neural networks (CNN), which are effective for processing audio data. The architecture of the model included several convolutional and fully connected layers. The ReLU activation function was used in all layers, except the last one, where the softmax function was used for the output of the final class [3].

The ReLU activation function (Rectified Linear Unit) is one of the most popular activation functions used in neural networks. It introduces nonlinearity into the model, allowing the neural network to learn and model more complex patterns.

ReLU is defined by the following formula: $f(x)=\max(0,x)$.

This means that the ReLU activation function returns the input if it is positive, otherwise it returns 0 [4].

The model was trained using the Adam optimization algorithm, using cross-entropy loss as the loss function. The batch size was set to 32, and the number of epochs - to 100. To prevent overfitting, early stopping was used, with a patience period of 10 epochs.

The Adam optimization algorithm (Adaptive Moment Estimation) is one of the most popular optimization methods for neural networks. It combines the advantages of two other optimization methods: RMSProp (Root Mean Square Propagation) and SGD (Stochastic Gradient Descent) with momentum [5].

The main parameters of the Adam algorithm include: ● Learning rate: this is the step with which the model updates weights in the learning process. Usually set in the range from 0.1 to 0.0001. In our researchThe document continues:

- Value of 0.001 was used.
- Beta1: this is a parameter that controls the smoothing rate of the first moment (the mean value of gradients).Usually set to 0.9.
- Beta2: this is a parameter that controls the smoothing rate of the second moment (uncorrected variance of gradients). Usually set to 0.999 [6].
- Epsilon: this is a very small number that is added to the denominator when updating weights to prevent division by zero. Set to 1e-8.

The model's accuracy was evaluated using 5-fold cross-validation. For each fold, accuracy, sensitivity, specificity, and F1-score were calculated, and then the average value of these metrics was calculated.

5-fold cross-validation is a model evaluation method in which the dataset is divided into 5 equal parts, or "folds". The model is trained on 4 folds, and then tested on 1 fold. This process is repeated 5 times, so that each fold is used as a test set once.

Accuracy, sensitivity, specificity, and F1-score are calculated for each of these 5 tests, and then the average value of these metrics is calculated [7].

These methods were chosen with the aim of developing an effective and automated system for evaluating the acoustic quality of premises. They allow the use of large volumes of acoustic data for training a model that can accurately predict acoustic quality based on this data. This can significantly simplify the process of evaluating the acoustic quality of premises, making it more accessible and efficient.

As a result of the conducted research, a deep learning model for automated evaluation of acoustic quality of premises was developed. The model was trained on a large dataset, which included various acoustic parameters of premises, such as reverberation time, loudness level, and others [8].

After training, the model was tested using 5-fold cross-validation. The average values of the metrics for evaluating the quality of the model were as follows: accuracy - 0.85, sensitivity - 0.83, specificity - 0.87, F1-score - 0.84. These results indicate the high ability of the model to correctly classify the acoustic quality of premises [9].

An analysis of the importance of the features used for training the model was conducted. The most important features turned out to be reverberation time and loudness level, which corresponds to the intuitive understanding of the acoustic quality of premises [10].

Python code for creating and training the deep learning model is provided in the document, as well as Python code using the scikit-learn library for conducting 5-fold cross-validation:

```
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = Sequential()
model.add(Dense(64, input_dim=10, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
# Налаштування оптимізатора Adam
adam = Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-8)
model.compile(loss='binary_crossentropy', optimizer=adam, metrics=['accuracy'])
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=100, batch_size=10)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall =recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
print(f'Precision: {precision}')
print(f'Recall: {recall}')
print(f'F1 Score: {f1}')

from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import make_scorer, accuracy_score, precision_score, recall_score, f1_score

scoring = {'accuracy' : make_scorer(accuracy_score),
 'precision' : make_scorer(precision_score),
 'recall' : make_scorer(recall_score),
 'f1_score' : make_scorer(f1_score)}

kfold = KFold(n_splits=5)
# Проведення крос-валідації
results = cross_val_score(model, X, y, cv=kfold, scoring=scoring)

mean_accuracy = results['test_accuracy'].mean()
mean_precision = results['test_precision'].mean()
mean_recall = results['test_recall'].mean()
mean_f1_score = results['test_f1_score'].mean()
```

DISCUSSION

This research presented a new approach to evaluating the acoustic quality of premises using deep learning models. This approach involves the use of large datasets containing various acoustic parameters and the application of algorithms for automated evaluation of acoustic quality based on these data. This can significantly simplify the process of evaluating the acoustic quality of premises, making it more accessible and efficient [11].

Despite the promising results, there are several areas where the model could be improved. One of these is the evaluation of the acoustic quality of premises with a high level of noise. The model showed lower accuracy in these cases, which may be due to the complexity of distinguishing between the effects of noise and other acoustic parameters. Future research could focus on improving the model's performance in these challenging conditions.

Another area for improvement is the interpretability of the model. While the model showed high accuracy, it is a "black box" that does not provide insights into the relationships between different acoustic parameters and the overall acoustic quality of premises. Future work could explore methods for increasing the interpretability of the model, such as the use of explainable AI techniques.

Despite these limitations, the research results confirm the potential of using deep learning in the field of acoustic design. The developed model can be used as a tool for automated evaluation of acoustic quality of premises, which can significantly simplify the process and make it more accessible to non-experts. This opens up new opportunities for further development and improvement of methods for automated evaluation of acoustic quality of premises, which may have important practical implications for this field.

CONCLUSION

This research presented a new approach to evaluating the acoustic quality of premises using deep learning. A model was developed and trained on a large dataset, which included various acoustic parameters. The model showed high accuracy, sensitivity, specificity, and F1-score, confirming its ability to correctly classify the acoustic quality of premises.

However, the research also identified several areas where the model could be improved, particularly in the evaluation of the acoustic quality of premises with a high level of noise and in increasing the interpretability of the model. Despite these challenges, the research results confirm the potential of using deep learning in the field of acoustic design.

The developed model can be used as a tool for automated evaluation of acoustic quality of premises, which can significantly simplify the process and make it more accessible to non-experts. This opens up new opportunities for further development and improvement of methods for automated evaluation of acoustic quality of premises, which may have important practical implications for this field."

Please note that this is a general translation and some technical terms may not be translated accurately. For a professional translation, consider hiring a professional translator.

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