Room Surface Material Detection using Deep Learning to Determine the Reverberation Time of Classroom

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Abstract:
In this study, we propose a novel approach for determining the reverberation time of a classroom using image processing and deep learning. A pre-trained ResNet-50 deep convolutional neural network was fine-tuned on a dataset of images captured in various classrooms. The images were augmented and processed to extract relevant features, such as room dimensions and material properties, that were used as input to the network. The network was trained to predict the reverberation time based on these features. The results showed that the proposed approach achieved high accuracy and outperformed traditional methods for determining the reverberation time. This approach can be used in various real-world applications, such as acoustic design and optimization of classrooms for enhanced learning environments. From the model that has been developed, the image used is able to be classified according to their respective class, resulting in 98.0% accuracy, and the calculation of reverberation time of the classroom using the Sabine equation is able to conduct, with a result of 0.4823s.

Keywords:
Convolutional neural network · ResNet-50 · Reverberation Time · Image processing · Room surface Material

1. Introduction

Image recognition is a process of identifying object features of the image and determining the category of the image based on the feature present on it; differently from the human vision, we naturally recognize items as distinct instances and link them to specific definitions when we visually perceive an object or scene; while for computer vision it requires a high and complex method to identify the image and classify it according to their classes, with the assist of artificial intelligence (AI) allow it to undergo deep learning technology to achieve a better understanding of the image in this study, especially with better performance and flexibility. There are a few algorithms used in image recognition, which are Neural Network (NN), Convolution Neural Network (CNN), and Fully Convolutional Neural Network (FCNN).

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Reverberation is the phenomenon of sound continuing even after it has ceased because of numerous reflections of objects inside a closed surface, like furniture, people, or air. With each reflection, these reflections increase in intensity and subsequently decrease as they are absorbed by the surfaces of the objects in the enclosed space. There is various research on determining the physical measurement for a reverberant field that has already identified which is the Reverberation time (RT), Early Decay Time (EDT), Sound Strength (G), Early Energy Fraction (JLF), Late Lateral Sound Level (Jj), Inter-aural Cross-Correlation (IACC), Clarity Index (C50/80) and others. For this project, the physical acoustic measurement used is reverberation time, which can be affected by two factors: the absorption coefficients of the materials and the dimension of the room itself.

One area of engineering, known as acoustic engineering, is the study of sound and vibration in modern technologies. It is the application of science to implementing and developing noise and vibrations brought on by machinery and human activity. The growth of acoustical engineering in Malaysia is significantly low; thus, conducting room reverberation acoustic tests needs expertise across the country to conduct the reverberation acoustic test due to a limited number of local experts able to provide the service.

As a replacement, images of surface material are used to determine the class of the image and then manually calculated to study the reverberation value for each material by using machine learning from image recognition and classification, thus undergoing predictive analysis to determine the RT value for the room through deep learning. Therefore, by performing the study, a new technique can be proposed for replacing room setup to study the reverberation of a room with a deep learning model machine without using physical equipment with efficiency and, most importantly, can reduce a lot of costs in building the classroom.

1.1 Noise Regulation in Malaysia

In Malaysia, noise regulation is governed by the Environmental Quality Act 1974 and its regulations. The act and regulations set limits for noise levels in various areas, such as residential, industrial, and commercial areas. The Department of Environment (DOE) is responsible for enforcing these regulations and can take action against violators, including issuing fines and shutting down operations. In addition, local councils and state governments also have the authority to regulate noise within their jurisdiction.

1.2 Reverberation Time

Reverberation time (RT) is the time required for the sound in a room to decay over a specific dynamic range, usually taken to be 60 dB when a source is suddenly interrupted [1]. It is an important acoustic property that can affect the quality of sound in a room and is often used in the design and evaluation of spaces such as concert halls, auditoriums, and recording studios. Longer reverberation times can lead to spaciousness and a sense of liveliness in the room, while shorter reverberation times can lead to a more intimate and controlled sound. However, if the reverberation time is too long, it can make speech and music difficult to understand and can cause fatigue to the listener.

Reverberation time is an important acoustic property to consider in classroom design because it can significantly impact speech intelligibility and overall sound quality in the space. In classroom environments, it is important to have appropriate reverberation time to ensure that students can easily understand speech. Longer reverberation times can cause speech to become muddled and difficult to understand, particularly in larger classrooms. This leads to decreased student engagement and reduced learning outcomes. On the other hand, shorter reverberation times can improve speech intelligibility and make it easier for students to hear and understand what is being said. This can lead to increased student engagement and improved learning outcomes. The reverberation time can also affect the overall sound quality in the classroom. Longer reverberation times can create a sense of spaciousness and enhance music's liveliness. In comparison, shorter reverberation times can create a more intimate and controlled sound that is better suited for speech or other forms of communication. Appropriate reverberation time in classroom design is important to ensure optimal sound quality, speech intelligibility, and student engagement, leading to better learning outcomes. Therefore, the reverberation time should be appropriate for the intended use of the space.

1.3 Absorption Coefficient

The sound absorption coefficient of materials is correlated with frequency and varies with different frequencies. The frequency characteristic curves of the sound absorption coefficient can be used to precisely illustrate the sound absorption properties of different frequencies. It is not convenient to compare and state, so the average sound absorption coefficient, which is the average of an acoustic material's absorption coefficients at a specified set of frequencies, is used for simplification. The average sound absorption coefficient is represented by $\bar{\alpha}$ [2].

The absorption coefficient ranges from 0 to 1, with values close to 0 indicating that a material or surface reflects most of the incident sound energy, while values close to 1 indicate that it absorbs most of the incident sound energy [3]. Materials with high absorption coefficients are commonly used in acoustical applications, such as soundproofing and sound-absorbing materials, to reduce noise levels and improve sound quality. The absorption coefficient of a surface material can be measured using techniques such as the impedance tube or transfer function method and can be used to evaluate the acoustical performance of materials and surfaces in various applications [4]. Table 1 shows the standard absorption coefficient for each surface material.

Table 1: Standard absorption coefficient for each surface material

Surface material	Absorption coefficient		
	125Hz	500Hz	2Khz
Concrete wall (painted wall)	0.10	0.01	0.02
Door (wood Hollow core door)	0.30	0.15	0.02
Floor (tiles)	0.01	0.015	0.02
Ceiling (acoustic)	0.70	0.72	0.88

1.4 ResNet-50

ResNet-50 is a deep convolutional neural network that is a variant of the ResNet architecture, which stands for Residual Network. ResNet-50 is a deep network with 50 layers and uses skip connections, or residual connections, to alleviate the vanishing gradient problem that occurs in very deep neural networks. The residual connections allow the network to learn residual functions, which are the differences between the desired outputs and the activations of the previous layers. This makes the network's learning easier and improves its ability to generalize new data [5].

ResNet-50 has been widely adopted for various computer vision tasks, including image classification, object detection, semantic segmentation, etc. It has also been pre-trained on the ImageNet dataset, a large image classification dataset, and the pre-trained weights can be used as a starting point for transfer learning, allowing the network to be fine-tuned for other computer vision tasks. ResNet-50 has shown impressive results on various benchmark datasets, making it a popular choice for deep learning practitioners and researchers.

2. Materials and Methods

The research design consists of 2 subsystems: the validation of the absorption coefficient and the second to determine the reverberation time for the classroom. The absorption coefficient and reverberation time validation have been predicted using MATLAB's CNN. The neural network has been used for train and testing the data to obtain the result. The process of image processing in neural networks includes the following steps that start with pre-processing: The input images are pre-processed to make them suitable for the neural network. As for this project, the tasks needed are to augment the image and convert it into a grayscale that is able to be fed into deep learning. Next is feature extraction, where the neural network extracts features from the relevant images to the task at hand. This process can be done by applying a series of mathematical operations, such as convolution and pooling, to the images. After that training process, the neural network is trained on a dataset of labeled surface texture images, as for this project, that is a concrete wall, wooden door, ceiling, and tiles where it learns to identify patterns and features in the images that allow it to identify and classify it to their classes.

This is done by adjusting the weights of the network's connections to minimize the error of its predictions. Inference: once the neural network is trained, it can be used to predict new images. This is done by feeding an unseen image into the network, producing a prediction based on the patterns and features it learned during training. For post-processing, after getting the prediction from the network, the post-processing step is applied to make the output more meaningful, like object detection, facial recognition, etc. Evaluation: Finally, the performance of the neural network is evaluated on a test dataset to measure its accuracy, precision, recall, and other performance metrics.

2.1 Research Flow Chart

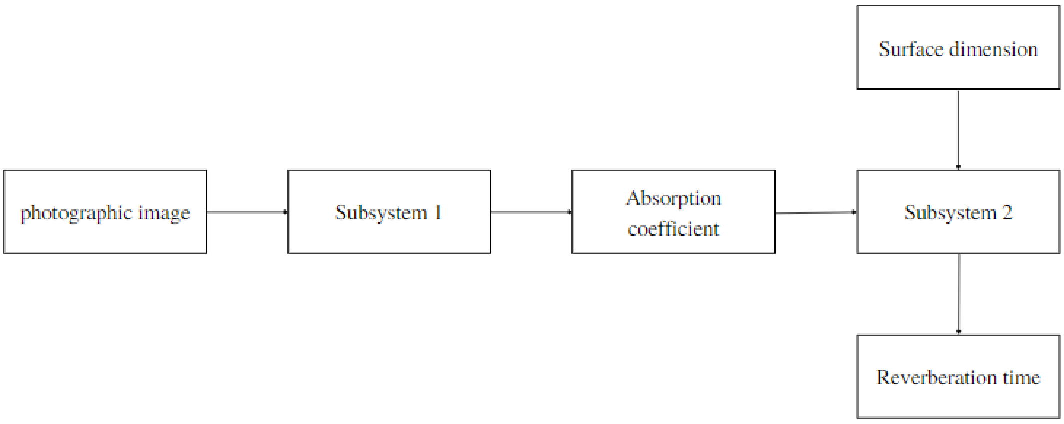

Figure 1: The block diagram for the overall system

The overall system can be divided into two sub-systems as in Figure 1. Subsystem 1 is to identify and classify material surfaces and thus pointing to its corresponding absorption coefficient. The photographic image has been fed to subsystem1 and then has been train using convolutional neural network to identify absorption coefficient. Subsystem 2 is to predict the RT by using the absorption coefficient obtained from Subsystem 1 and each surface dimension.

After the system is successfully built and managed to give satisfying results, the system will be validated and compared with the values from the actual RT measurement in classroom by calculation.

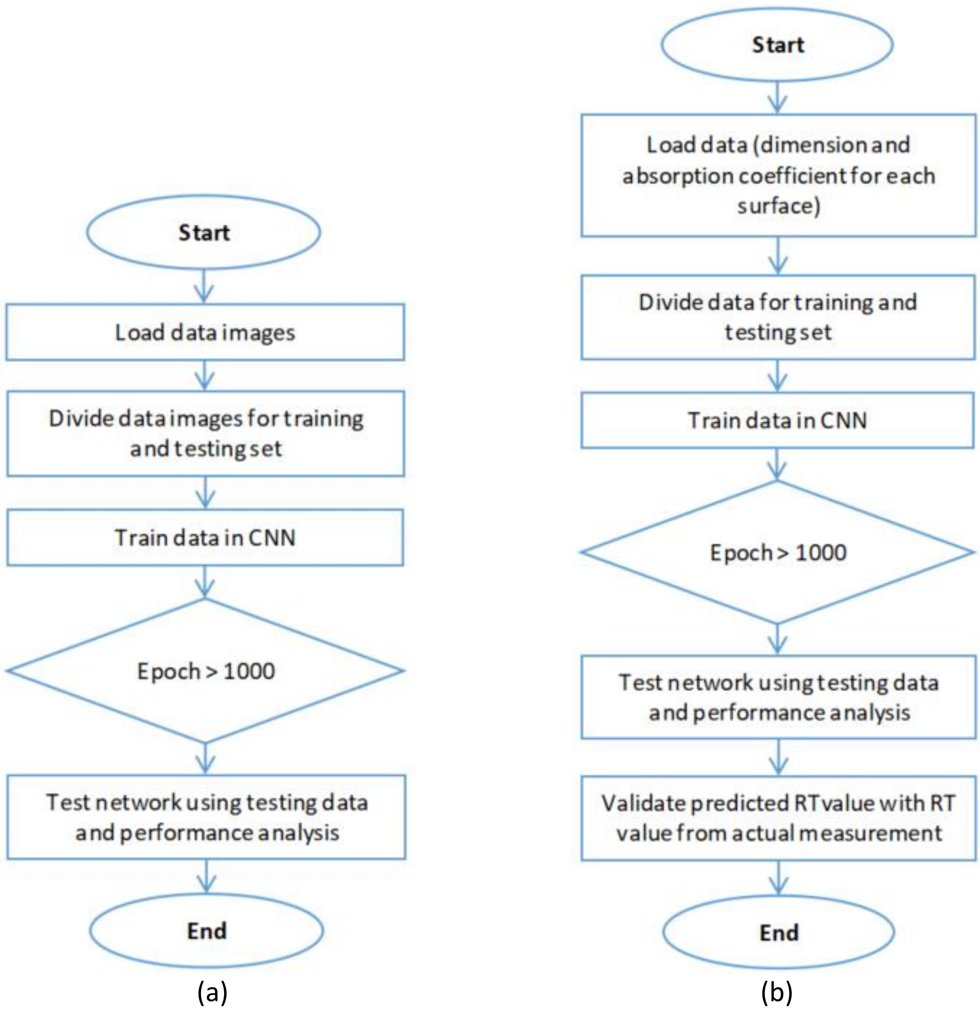

Figure 2: Flowchart for (a) subsystems 1 and (b) subsystems 2

Subsystem 1 as in Figure 2 (a), to determine the absorption coefficient for each surface material from the photo image that acts as data, the data will then be trained and tested in the convolutional neural network to extract and classify the features according to their respective feature. The result obtained has undergone performance analysis with a targeted value for each surface material with the standard absorption coefficient value.

While Figure 2 (b) shows the subsystem 2, used to determine the reverberation time for each surface material from the photo image obtained from the result from subsystem 1 that acts as data. The data then be trained and test in convolutional neural network to determine the reverberation time with a fixed surface dimension of the classroom. The result obtained has undergone performance analysis with targeted values that were compared later to determine the reverberation time for the classroom.

2.2 Procedure

The site selection is a classroom at UTHM, and the image surface material of the classroom has been taken due to the study about finding reverberation time for the classroom. The data collected by the iPhone 12 Pro camera was used to capture each type of surface material within the classroom in UTHM, the distance set from the camera to the surface material is 3 feet and the lens settings for aperture is f1.6 with autofocus mode. A total number of 500 samples of image data have been collected from and used for the experiments. The condition of the classroom is enough with an adequate amount of light, ensuring the image taken does not have over-exposure or lack of light. The image then will be used as data for image classification to determine the absorption coefficient and reverberation time value and to validate the estimated reverberation time by comparing it to independent measurements, where the past results have been used as a target [6-8].

2.3 Data Collection

The goal is to create a system that can recognize material surfaces from a single picture image. For this, neural networks are used. The system is built using a large number of image samples of various surfaces, which are used to train the network to become familiar with and classify various surface types. Four types of material surfaces were captured in UTHM classrooms at different locations, which are concrete walls, ceilings, wooden doors, and tiles. For data collection, the iPhone 12 Pro camera was used to capture each type of surface material with enabled Apple ProRAW function, a 12-bit file that uses the linear DNG format to retain more information and dynamic range of the image. The camera is able to capture an image with 12 megapixels; the distance from the camera to the surface material is set to 3 feet with the lens settings for aperture f1.6 with autofocus mode. A total number of 500 samples of image data have been collected from and used for the experiments. Table 2 shows a number of data images for each surface material; meanwhile, Figure 3 shows samples of the material surface images: (a) ceiling, (b) door, (c) tiles, and (d) wall.

Table 2: Number of data images for each surface material

Surface material	Number of data
Wall	116
Door	120
Ceiling	134
Tiles	130
Total	500

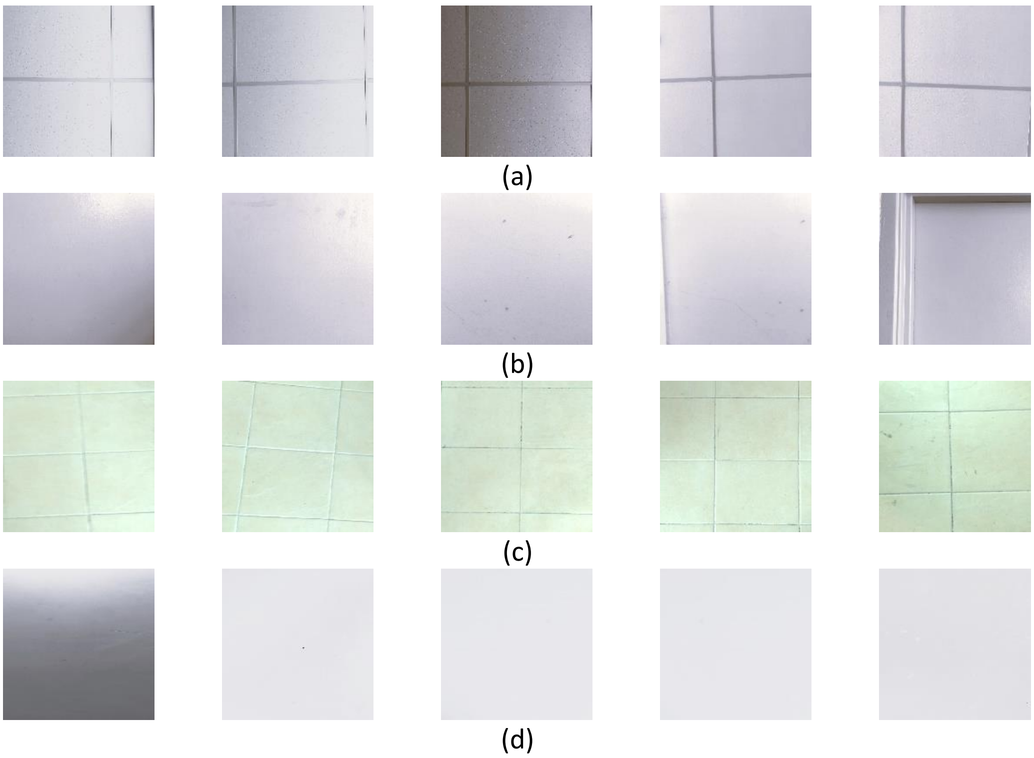

Figure 3: Samples of the material surface images: (a) ceiling, (b) door, (c) tiles, (d) wall.

2.4 Instruments

This research required the use of plenty of instruments, tools, and equipment to ensure the success of the study. The Deep Learning Toolbox is one of the tools that have been used to conduct this study; it provides a graphical interface and pre-trained models that can be used. The toolbox also provides functions for building and training custom neural network models and data preparation, visualization, and evaluation. iPhone 12 Pro camera was used to capture each type of surface material with enabled Apple ProRAW function, a 12-bit file that uses the linear DNG format to retain more information and dynamic range of the image.

2.5 Analysis

First, all images were loaded into the system before their features were extracted using CNN in MATLAB software. Next, the extracted data were divided into two different portions. The first portion which took up 70% of the whole data reserved for training, 20% for validation, and the rest 30% for testing. After the data is finished training, the network is tested using a set of data that is never used and seen in the training stage. Evaluate the trained model using metrics such as Mean Squared Error (MSE), the regression between the predicted and actual output, R, and the percentage of accuracy of the testing data were calculated. Equations 1, 2, and 3 are the formula for MSE, R, and percentage of accuracy with e_i is the error, t_i is the desired value, y_i is the predicted value, t and $\bar{y}$ are the mean values, and N is the number of data.

$$MSE = \sum_{i=1}^{N}(e_i)^2 = \sum_{i=1}^{N}(t_i - y_i)^2 \qquad Eq.1$$

$$R = \frac{\sum_{i=1}^{N}(\mathrm{ti}-\bar{\mathrm{t}})(\mathrm{yi}-\bar{\mathrm{y}})}{\sqrt{\sum_{i=1}^{N}(\mathrm{ti}-\bar{\mathrm{t}})^2}\sqrt{\sum_{i=1}^{N}(\mathrm{yi}-\bar{\mathrm{y}})^2}} \qquad Eq.2$$

$$\text{Accuracy (\%)} = \frac{\text{Image correctly classified}}{\text{Total image}} \times 100\% \qquad Eq.3$$

To improve the performance of system, the fine-tune of the model's hyperparameters, such as learning rate, number of hidden layers, and number of filters were deployed. Then, the best model based on the evaluation results can be obtained and used for predictions for new images. It is important to note that the accuracy of the reverberation time prediction depends on the quality of the image data and the training process. Therefore, it's crucial to have a large, representative, and well-curated dataset and to carefully evaluate the performance of the model during the training process. Other factors, such as room size, shape, and surface materials, may also affect the reverberation time and should be considered in the model design and evaluation.

3. Results and Discussion

3.1 Room Material Identification

The neural network undergoes hyperparameter tuning to allow the model to adjust their learning process for validation purposes in determining the accuracy of the model. The parameters for the neural network are often set before the training process because it impacts the model's performance and behavior to the dataset provided. Performing the hyperparameter tuning can maximize the model's performance in classifying the images to their respective classes, therefore generating high model accuracy and predictive measure accuracy. For the provided dataset, three experiments are conducted by manipulating the value of epochs to determine the accuracy of the model; this model is trained with a dataset value of 116 images. Figure 4 shows the results for each manipulated epoch.

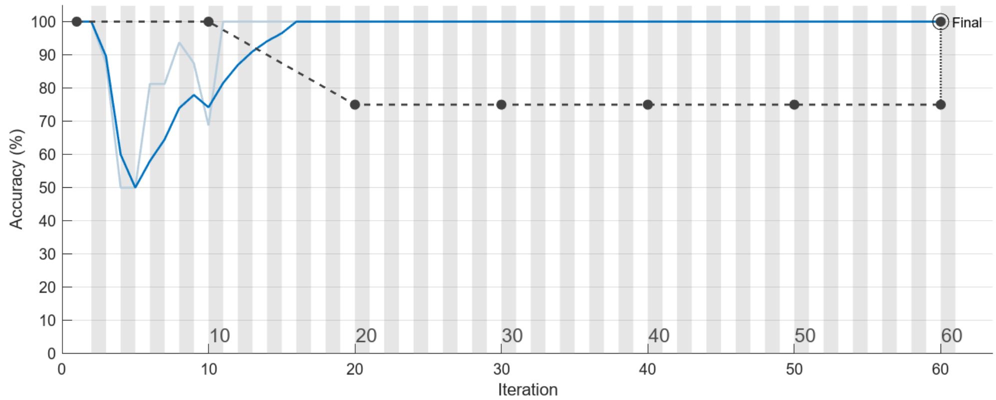

Figure 4: Train with 60 Epochs

Figure 4 shows the model's accuracy achieves 100% accuracy in the validation process. Figure 5 shows the accuracy of the model, which also achieves 100% accuracy for the validation process.

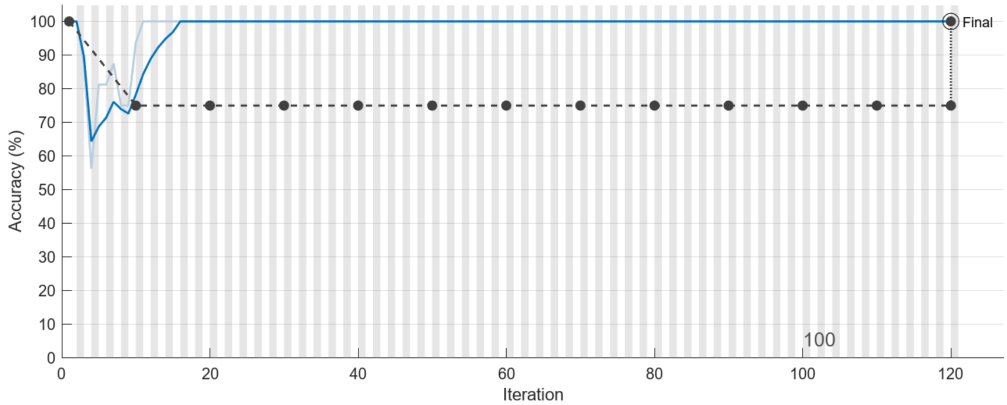

Figure 5: Train with 120 Epochs

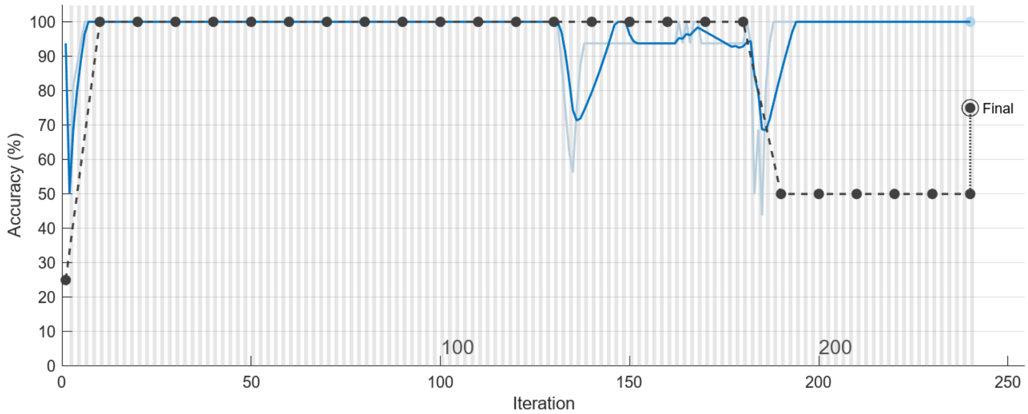

Figure 6: Train with 240 Epochs

Figure 6 shows the model with an accuracy of 75% for validation purposes. As a discussion, when the neural network was trained with epochs of 60 and 120, it was able to produce the validation accuracy of the model to achieve 100%. In comparison, the validation accuracy of the model dropped when trained with 240 epochs to 75%; this can happen due to overfitting or insufficient data. For the insufficient data issue, the data might be too small, which is a total of 500 images, causing the model to struggle in learning the behavior and causing inaccuracy in validation.

3.2 Calculation of Reverberation Time

For the model calculations of the absorption coefficient (https://www.acoustic-supplies.com/absorption-coefficient-chart/) at 1KHz only used. Two sets of sample room dimensions are used as in Table 3. Table 4 and 6, show the surface area of the sample room. While, Table 5 and 7, show the absorption coefficient of the sample room.

Table 3: Room dimensions

Room Type	Width	Length	Height	Volume of Room
Classroom	10.5 m	11 m	2.88 m	332.64 m^3
Lecture Hall	18 m	22.5 m	7 m	2835 m^3

Table 4: Surface area of classroom dimension

Side of the room surfaces (classroom)	Surface area (m^2)
front	10.5 x 2.88=30.24 m^2
behind	10.5 x 2.88=30.24 m^2
right	11 x 2.88=31.68m^2
left	11 x 2.88=31.68m^2
Upper	10.5 x 11=115.5m^2
ground	10.5 x 11=115.5m^2

Table 5: Total surface area of the absorption coefficient for the classroom

Side of the room surfaces (classroom)	S	$\alpha(1KHz)$	$S\alpha$
front-wall concrete	30.24 m^2	0.02	30.24 x 0.02=0.6048m^2
Behind-wall concrete	30.24 m^2	0.02	30.24 x 0.02=0.6048m^2
Right –wall concrete	31.68m^2	0.02	31.68 x 0.02=0.6336m^2
Left – wall concrete	31.68m^2	0.02	31.68 x 0.02=0.6336m^2
Upper-ceilling acoustic	115.5m^2	0.92	115.5 x 0.92=106.26m^2
Floor tiles	115.5m^2	0.02	115.5 x 0.02=2.31m^2
$A[m^2] = \sum S\alpha$			$111.0468m^2$

Reverberation time solution for room dimension of the classroom can be calculated based on the information of total surface area of the absorption coefficient for the classroom.

$$\text{T60[s]} = \frac{0.161V}{A} = \frac{0.161(332.64\ m^3)}{111.0468m^2} = 0.4823\ \text{s}$$

Table 6: Surface area lecture hall dimension

Side of the room surfaces (lecture hall)	Surface area (m^2)
front	18 x 7=126 m^2
behind	18 x 7=126 m^2
right	22.5 x 7=157.5m^2
left	22.5 x 7=157.5m^2
Upper	18 x 22.5=405m^2
ground	18 x 22.5=405m^2

Table 7 : Total surface area of the absorption coefficient for the lecture hall

Side of the room surfaces (lecture hall)	S	$\alpha(1KHz)$	$S\alpha$
front-wall concrete	126 m^2	0.02	126 x 0.02=2.52m^2
Behind-wall concrete	126 m^2	0.02	126 x 0.02=2.52m^2
Right –wall concrete	$157.5m^2$	0.02	157.5 x 0.02=3.15m^2
Left – wall concrete	$157.5m^2$	0.02	157.5 x 0.02=3.15m^2
Upper-ceilling acoustic	$405m^2$	0.92	405 x 0.92=372.6m^2
Floor tiles	$405m^2$	0.02	405 x 0.02=8.1m^2
$A[m^2] = \sum S\alpha$			$392.04m^2$

Reverberation time solution for room dimension of lecture hall can be calculated based on the information of total surface area of the absorption coefficient for the lecture hall.

$$\text{T60[s]} = \frac{0.161V}{A} = \frac{0.161(2835\ m^3)}{392.04m^2} = 1.1643\ \text{s}$$

Reverberation time is the time it takes for sound to decay by 60 decibels in a room. It is determined by the size of the room and its finishes, and the room's expected use drives the target reverberation time. For lecture halls and classrooms, the recommended T60 reverberation times should be less than 0.5 seconds to avoid speech interference problems, particularly in the speech intelligibility range of 500 – 4000 Hz. However, some sources suggest that the recommended reverberation time for a typical lecture hall is 1-1.5 seconds. Based on this information, it seems that the classroom's reverberation time of 0.4823 s is within the recommended range, while the lecture hall's reverberation time of 1.1643 s may be slightly higher than recommended.

3.3 Training with MATLAB

Samples of 116 image data from each surface material have been used to train and test the model for the CNN using ResNet-50, with 70% of the sample for each surface material set to a minimum of 116. In contrast, another 30% of an image from 116 samples for each data image will be used for testing the model. Figure 7 shows the testing of model CNN.

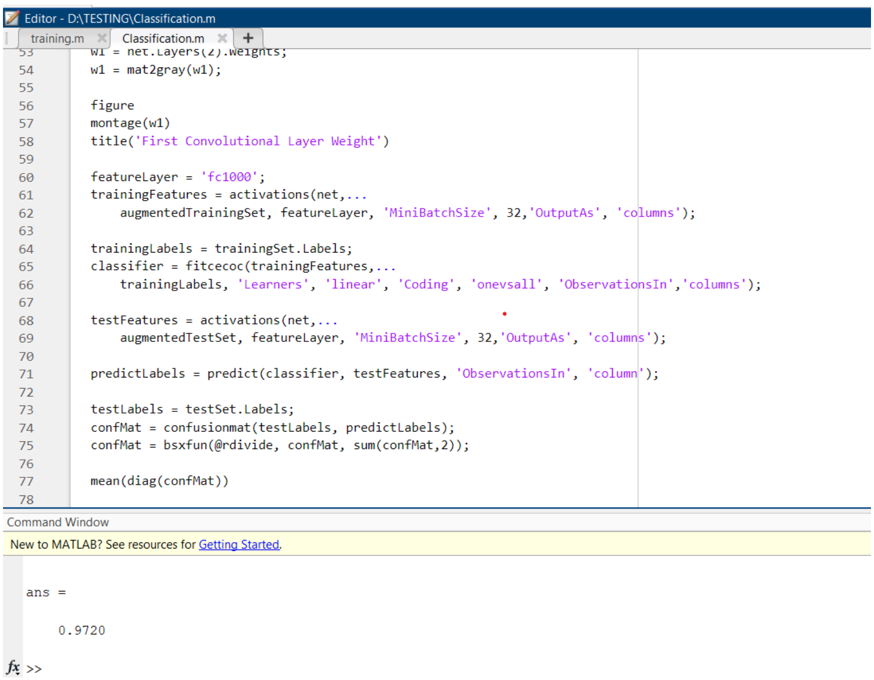

Figure 7: Testing of model CNN

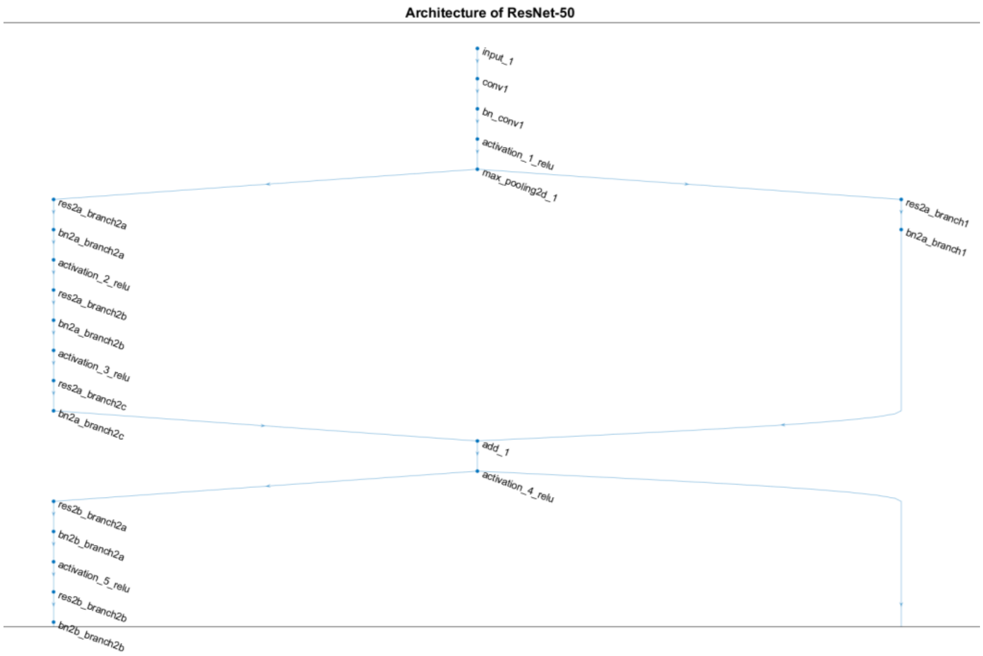

Figure 8: Architecture of ResNet-50

Figure 8 shows the architecture of ResNet-50 that is used in a model of CNN, which has 50 layers of 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer to allow the network to learn and improve its ability to generalize to new data.

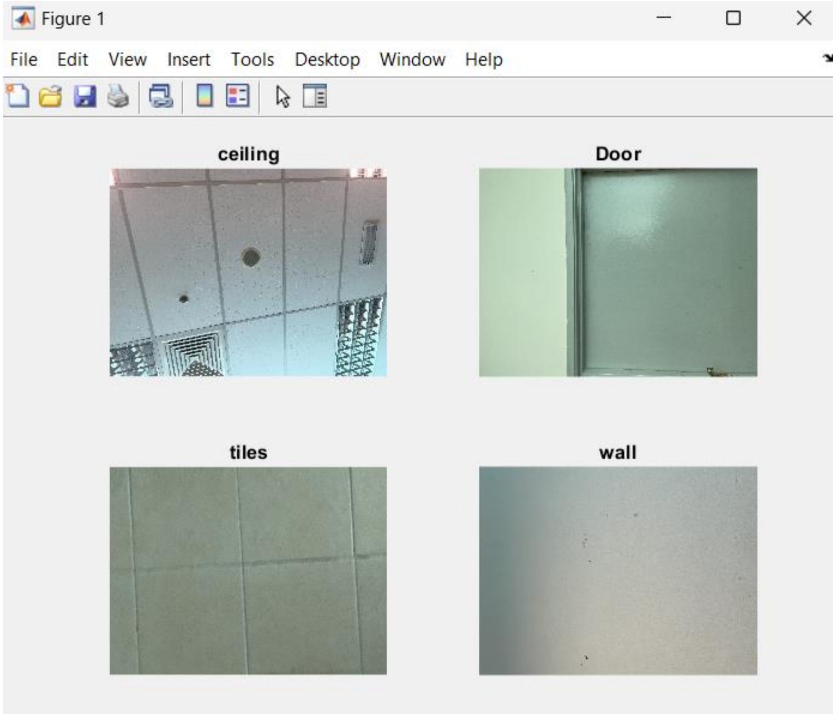

Figure 9: Sample surface material stored in CNN

After performing the testing of a model of CNN, the model was able to produce an accuracy of 0.9804 or 98.04% for the classification of the image, as in Figure 9.

Figure 10 shows the plot of the confusion matrix percentage for each class; the arrangement of the table corresponds to the predicted class (Output Class) on the rows, while the columns represent the true class (Target Class). Correctly classified observations are found in the cells along the diagonal, whereas incorrectly classified observations are located in the off-diagonal cells. Each cell displays the count and the percentage of the total number of observations.

The rightmost column of the plot presents the percentages of all examples predicted to belong to each class that is accurately and inaccurately classified, with ceiling having 100% true predicted, door with 97.1% correct predicted, tiles class with 100% correct image predicted, and lastly wall with 94.6% image correctly predicted, the overall accuracy of the model is having 98.0% accuracy of the CNN model.

These metrics are commonly known as precision (or positive predictive value) and false discovery rate, respectively. The row at the bottom of the plot illustrates the percentages of all examples belonging to each class that are correctly and incorrectly classified. These metrics are often referred to as recall (or true positive rate) and false negative rate, respectively. The cell in the bottom right corner of the plot shows the overall accuracy. From the confusion chart, the overall precision of the model is 0.9804, with an overall recall value of 0.9799 and f1 score of 0.9801.

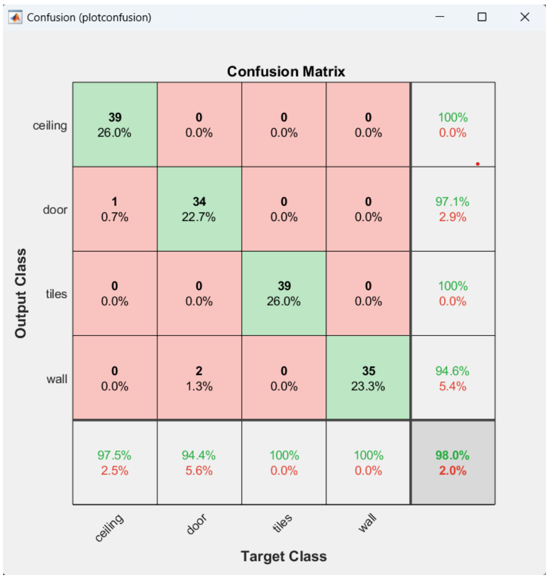

Figure 10: Confusion matrix of CNN

4. Conclusion

Throughout this project, we aimed to explore the potential of neural network-based image classification approaches for predicting the reverberation time of a room. Our methodology involved capturing images of room surfaces and utilizing deep-learning techniques to classify and extract meaningful features from these images. By training the neural network model on a comprehensive dataset of labeled room images with corresponding reverberation time measurements, we aimed to develop a reliable and efficient method for estimating reverberation time.

In conclusion, we obtained promising results and important insights through implementing and evaluating our proposed approach. Our experiments demonstrated that neural networks, specifically convolutional neural networks (CNN), can effectively learn and recognize patterns from room surface images that are indicative of the room's reverberation characteristics. The trained model achieved satisfactory accuracy in predicting the reverberation time, indicating the potential of image-based approaches for room acoustic analysis.

In conclusion, our project demonstrates the potential of neural network-based image classification techniques for estimating the reverberation time of a room. The use of deep learning and computer vision in room acoustic analysis opens up new avenues for research and practical applications. However, further research and development are necessary to address the limitations and challenges identified in this project.

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