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Analysis and Design of Deep Neural Network to Detect Damage of the Four-Floor Building Structure

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ABSTRACT

Stress or exessive tension can damaged civic building structure. Damage at civic builiding structure can cause fatal accident that take a lot of casualties. That’s why it’s important to do prevention with structural health monitoring. At this research writter try to find best deep neural network arcitecture for predicting damage at three-stories buliding with classifying the vibration data to three class that is the structure is healthy, there is stiffness reduction at building structure, and the structure is damaged. After experimenting on couple architecture, the writter can conclude that convolutional neural network architecture, VGG19 as the best architecture for solving problems at this research, based on speed, recall at damaged structure class, and better prediction accurasy (82.76%).

Key words : Deep Neural Network, Machine Learning, Structural Health Monitoring.

1. INTRODUCTION

Excessive stress or stress can cause the building structure to be damaged. Damage to building structures can cause fatal disasters that will take many victims, since concrete is the mostly used construction material all over the world [1]. One example is the accident in Mumbai, India on August 2017 the collapse of the 4-story building that killed at least 12 people were killed and 15 others were injured.

This incident happened one of them due to inadequate supervision of the condition of the building structure. In recent years, automatic monitoring systems (known as Structural Health Monitoring (SHM)) have increasingly applied in research, especially those related to structural problems both for bridges, planes, high rise buildings, post-earthquake structures, etc.

Structural Health Monitoring is defined as the process of applying damage detection to infrastructure techniques. Structural Health Monitoring attracts a lot of attention because it has the potential to simplify the process of supervision and cost savings in individual buildings or structures such as a 4-story building. This system is considered fast and efficient when compared to manual systems because it uses sensors that make it possible to conduct vibration data retrieval on individual buildings or structures. Vibration data show signs of dynamic behavior structures that are widely known to be sensitive to damage.

Automatic monitoring systems have become possible using a machine learning technique in which a computational model that links structural response data with fundamental integrity data established. This can be done if structural response data that is sensitive to damage is available in abundant or high-dimensional quantities.

According to [2] systems, detecting structural damage involves two processes, namely feature collection and feature classification. Typically feature collection requires extensive computer computing, which prevents traditional ways of doing SHM. Moreover, in many cases, the classical methods fail to translate the signal obtained accurately, which is so large that it causes poor accuracy of the classification. To overcome this issue, they researched to produce a fast and accurate damage detection system using a 1-dimensional Convolutional Neural Network (CNN). The study resulted in initial experiments to verify their proposed CNN approach.

In general, the way SHM works based on vibration divided into three stages. The first stage is a structural vibration data system at several measurement points using several sensors. These data are generally very long. Then, the system will reduce these data to several features that are sensitive to damage to the structure. Finally, the system will predict the level and position of damage using the computational intelligence algorithm.

In this study, the authors will design a deep neural network that can detect damage to composite plate structures. The deep neural network is a type of neural network that takes an input and has more than one hidden layer. Additionally, it will get an output class, which in this case will be separated into three categories, namely, the structure is declared healthy, changes in tension in the construction, or damage to the structure.

Based on the background that has been described previously, the problem to be discussed in this study is what the best deep neural network architecture is for predicting damage to a 4-story building structure?

To answer the problem, the writer has the following initial hypothesis. Preprocessing received data will greatly assist this research. The highest and lowest values of the statistical results are the most critical features of the data obtained. The prediction model will overfitting, the amount of recall in the class of damaged building structures will be the primary consideration for designing a deep neural network architecture.

The scope of this study is limited to the data used in this study is data derived from simulation results because of the high cost involved if the data taken from real objects, the data considered in this study are only vibration data, neural network design will be done with the Python programming language,

Based on the scope and formulation of the problem presented, the purpose of the thesis preparation is to build a deep neural network that can predict damage to the 4-story building structure based on vibration data. The benefits of this research are as follows: Can predict the damage that occurs in a 4-story building structure based on vibration, Can prevent damage to structures in 4-story buildings in specific structures, Can be used as a comparison for calculations that will be used in other studies.

2. RESEARCH METHODOLOGY

The framework of thinking in this study will be divided into several stages, namely:

1. Formulating the problem
   Activities to be carried out in this section are to collect and identify problems to be studied and determine the limits of the problem be solved
2. Literature Studies
   The activity that will be carried out in this section is to search for information (data and formulations) through books, journals, official websites, and papers in the design of neural network architecture.
3. Collecting Data
   At this stage, the authors search for data sets of objects that will be used in this study.
4. Preprocessing Data
   After getting the data set of the desired object, the writer processes the data so that the data is prepared by a neural network and removes unwanted noise.
5. Neural Network Architecture Design
   In this activity, the authors design the architecture of neural networks and determine the amount of manipulation performed on the data.
6. Training
   At this stage, the authors conduct training on neural networks.
7. Testing and Comparing
   This activity is to determine the level of success of the architecture that has been made by way of operating several architectures that have been created.
8. Conclusion
   At this stage, the authors will draw conclusions from the results of previous studies conducted.

This research will be divided into several stages to answer the problems that have been outlined in chapter 1, namely the preparation stage, data collection, data processing, design architecture, training and testing phase, and concluding.

The preparation phase consists of 2 parts; the writer will identify the problem and study literature. Based on the background described in 1.1, the issue to be resolved from this research is detecting damage to the 4-story building structure using a deep neural network. Then the results will be classified into three classes, namely healthy building structures, changes in tension in the structure, and damage to the building structure.

In the next stage, the author will conduct a literary study that will be the basis or reference in the completion of this thesis. The topic that will be reviewed is about structural health monitoring (Structural Health Monitoring, SHM) for 4-story buildings and deep neural networks.
Initially, numerical data was received using 5 degrees of freedom (DOF) based on research conducted by [3] for Los Alamos National Laboratory. This numerical data is the result of vibration signal recording. The represented signal is an acceleration of historical data in time series. The 4-story building structure used can be seen in Figure 3.3. The 4-story building model is made of poles and plates made of aluminum. The model is combined by tightening using bolts, which can still allow movement in the x-direction only.

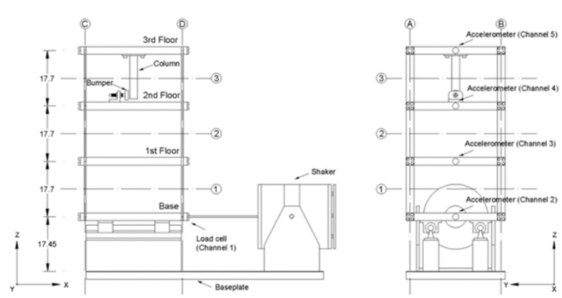

Figure 1: Story Building Model Used

The vibration data is recorded using an accelerometer on each floor. The vibration data is recorded within 25.6 seconds. The vibration data is recorded every 3,124 milliseconds. Thus, this data has a length of 8192. Data are classified into three classes, healthy building structures, building structures changes in tension, and damage to building structures. The author gives a gap in the column to simulate a difference due to cracking and replaces the phonation pole to affect the occurrence of strain changes. The damage that occurs is generally in the form of cracks in the structure of the model. A comparison of broken vibration graphics for each class can be seen in Figure 2.

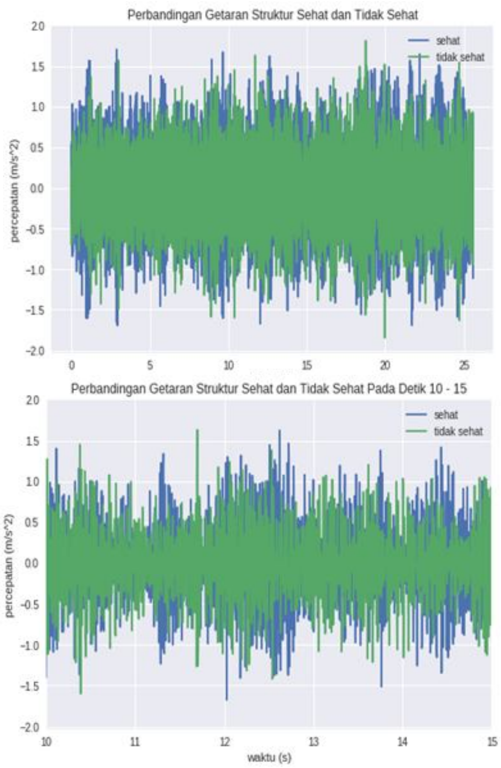

Figure 2: Graphic Comparison of Healthy and Unhealthy Class Vibrations

The data received is numerical data, which has five columns and 8192 rows, each column representing one recording location. The contents of the data can be seen in Figure 3.5. Each class has 10 data so that each category of writers has 50 data with a length of 8192.

In this study, after the vibration data obtained from the simulation, then the next data will be done preprocessing. The goal is to filter vibration data and eliminate noise. In Structural Health Monitoring (SHM), signals can be represented as historical data from the removal of observation points. First, the data is filtered using a Butterworth filter, taking frequencies from 5-100 Hz. This is done because data at frequencies 0-5 Hz and 100-160 Hz are considered to have no significant effect because there are not many changes that occur at that frequency.

Next, in this thesis, F-statistic is used as a feature of damage-sensitive. Data from the power spectrum density (PSD) obtained is required by following the procedure from Bartlett’s Method. Bartlett's Method calculates the PSD signal by calculating the average PSD of its sub-signals. PSD results will be far more reliable and not too sensitive to signal interference. However, this method will only apply to long signals. The number of K windows used in this thesis is 14. The complete PSD construction has been explained in 2.6.1.

After getting the PSD, we have been able to calculate Statistics. Data from Fstatistik symbolizes the vibration conditions in the data; when the value of f-statistic is getting closer to 1, then the situation can be said to be healthy if the numbers show otherwise it can be said to be damaged.The final step is to build the upper and lower limits of statistics so that they can categorize PSD changes as significant or not. The lower limit is the minimum value of f-statistic at certain DoF, and the upper limit is the maximum value of the f-statistic at a specific DoF. Fmax and Fmin are thought to be essential features of statistics, data other than Fmax and Fmin are insignificant data on this system.
In this study, there are several deep neural network architectures used. Following is the design used in this study:
1. Naïve deep neural network
Naïve deep neural network (DNN) is an architecture created by the author for use in this study. Naïve DNN will be used to classify data in the form of Fstatistik and Fstatistik max & min. In this study, the author will test several DNN architectures with several different hidden layers, ranging from 5 to 8 hidden layers. But in general, the DNN architecture will begin with the input layer, followed by a hidden layer using the sigmoid activation function; the last output layer will use the softmax activation function to classify classes. The naive DNN architecture can be seen in Figure 3.

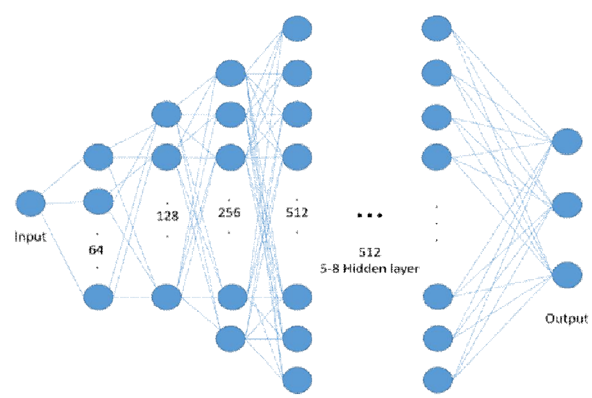

Figure 3: Architecture naïve deep neural network

2. Naïve Convolutional Neural Network

Naïve Convolutional Neural Network (CNN) is also an architecture that will be created by the author. Naïve CNN will only be used to classify data in the form of Statistics, in contrast to Naïve DNN because the length of the data after the data is processed to become Statistics is 257 while the range of the data after the data is processed to become statistic max & min is 2 so that the data after being processed is max & min, not statistic ideal to be classified using CNN. The primary purpose of using CNN to classify data on Statistics is to look for features that are considered essential to detect damage to a 4-story building.

Naïve CNN in this study will have nine layers consisting of an input layer, five convolution layers, two fully connected layers, and an output layer. The Naïve CNN used in this study is a one-dimensional CNN. The five convolution layers have the same specifications, each convolution layer has a large filter three, and every time it passes through the convolution layer a max-pooling operation will be carried out. 2 fully connected layers will have 4096 nodes, and the output layer will use the softmax activation function to classify classes. The configuration used by the CNN architecture can be seen in Table 3.1.

3. VGG19

Like Naïve CNN, VGG19 will only be used in data in the form of statistics. VGG19 is one of the famous CNN architects and has high accuracy when classifying images with a size of 224 x 224 [4]. This research will use the VGG19 architecture but in the original architecture, VGG19 is a 2-dimensional CNN architecture. The author made modifications to the VGG19 architecture, so that VGG19 is a 1-dimensional CNN that can be illustrated by Figure 4.

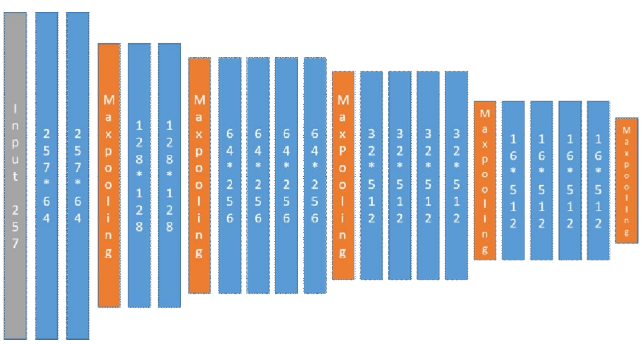

Figure 4: Modified Architecture of VGG19

VGG19 used in this study has the same number of layers, filter sizes, and the number of nodes as the original VGG19. The configuration that will be used on the CNN architecture will be explained in Table 1.

Table 1: Configuration on CNN architecture
Table 1 has the format <layer type><filter size> - <number of nodes>

Naïve	*Modified* VGG19
Input-257	
conv3-64	conv3-64
	conv3-64
max pooling	
conv3-128	conv3-128
	conv3-128
max pooling	
conv3-256	conv3-256
	conv3-256
	conv3-256
	conv3-256
max pooling	
conv3-512	conv3-512
	conv3-512
	conv3-512
	conv3-512
max pooling	
conv3-512	conv3-512
	conv3-512
	conv3-512
	conv3-512
max pooling	
FC-4096	
FC-4096	
Output	

In order to get the most optimal neural network architecture for the problem in this study, the author will train neural networks to be able to detect and classify damage to 4-story building structures. At this stage, the data will be divided into training datasets and testing datasets with a ratio of 9: 1 from a total of 1,450 data that will be optimized with ADAM, which has a learning rate of 10^{-3}.
Tests will be carried out several times with the same steps to ensure the model is not only suitable for specific data. At the training stage steps will be carried out as follows:

a) The system will read the training dataset and then randomly collect data for the training process.
b) The number of training dataset takes randomly will be adjusted to the batch size that has been defined as constant value.
c) Then step (b) will be done repeatedly as many batches as where the batches itself is also a constant value and for one batch will be done as much as the epoch training process.
d) At the end of the training process, a score will be obtained from $\vec{w}$ is in the form of vector and value b is in the form of scalar.
e) Testing dataset will be tested using value of $\vec{w}$ and b that have been obtained from training process.
f) To conclude, the writer will do an analysis. The analysis will start from the the preprocessing stage to the training and testing phase. The result of the study will be used to conclude to answer the problems previously described by the authors in chapter 1.

The analysis will first be done from the comparison of orders used on the bandpass filter, whether the filter does not become damaged if specific orders are used. Next, the writer will classify the level of damage in the 4-story building by using the maximum and minimum statistics. The writer will compare several naïve deep neural network architectures. Analysis of the performance of naïve deep neural network architectures will be performed based on a confusion matrix and model accuracy graph.

After obtaining an architecture that is considered valid for classifying damage to a 4-story building using the Fstatistik features maximum and minimum. Next, we will try the same steps using all statistical data using the naïve neural network architecture, naïve convolutional neural network, and VGG19. From these results and analysis, the writer will conclude this study.

3. RESULT AND DISCUSSION

The author will classify the features of the Maximum and Minimum Statistics (FMM) using the DNN architecture, as shown in Figure 3.

Table 2: Comparison of Training and Testing Accuracy by Using the FMM Feature

%	Amount of Hidden Layers			
	5	6	7	8
Training	66.05	72.41	66.89	66.90
Testing	71.72	73.33	64.83	65.52

From Table 2, it can be seen that the architecture using six hidden layers is the best architecture of this experiment. For further analysis, the authors make a confusion matrix of the architecture that can be seen in Table 3.

Table 3: Confusion Matrix DNN Architecture with 6 Hidden Layers Using the FMM Feature

	Prediction				Recall (%)
	Class	1	2	3	
Facts	1	33	8	0	78.57
	2	0	44	7	73.33
	3	9	16	28	63.64
Precision (%)		78.57	86.275	52.83	

From Table 3, it is known that architecture has an average precision of 73.33% and an average recall of 73.20%. Although DNN architecture with six hidden layers has the highest accuracy, the accuracy of the architecture is still below 80%; the architecture cannot be said to be suitable for use on this problem.

Because the architecture in the previous experiment still cannot be said to solve the problem that has been described in chapter 1, the writer must look for other alternatives to solve the problem. The FMM feature is indeed one of the crucial elements that can be obtained from the Statistics, but based on the results above, the features of the FMM cannot be used as the sole reference for classifying damage to a 4-story building structure.

Machine learning is undoubtedly the best solution for extracting features, especially deep neural networks. DNN architecture will certainly look for features that are considered necessary in the classification of damage to the structure of this 4-story building. The DNN architecture that will be used in this experiment is the naïve deep neural network architecture, the naïve convolutional neural network, and VGG19.

- Naïve Deep Neural Network

First, the author will use the same Naïve DNN architecture as the previous experiment, namely the DNN architecture outlined in Figure 3.

Table 4: Comparison of Training and Testing Accuracy by Using

	Prediction				Recall (%)
	Class	1	2	3	
Facts	1	35	0	14	71.43
	2	0	39	10	79.59
	3	1	0	46	97.87
Precision (%)		97.22	100	76.67	

Statistical Features

From Table 4, it can be seen that DNN architecture with 5 or 6 has higher accuracy. But as for the reasons explained earlier, architecture with five hidden layers is slightly overfitted, so it can be said that after two experiments, DNN architecture with six hidden layers is the best architecture to classify damage to 4-story building structures. For further analysis, the authors make a confusion matrix of the architecture that can be seen
in Table 5.

Table 5: Confusion Matrix DNN Architecture with 6 Hidden

%	Amount of Hidden Layers			
	5	6	7	8
Training	85.20	85.90	83.19	70.80
Testing	87.76	84.14	82.46	68.97

Layers Using the Statistical Features

- Naïve Convolutional Neural Network

Convolutional neural networks (CNN) are known to be magnificent architectures in searching for features, which is why the author decided to experiment with this architecture. Training in this experiment will be carried out using the parameters in Table 1.

The accuracy using training data is 87.20%, while when using testing data is 82.76%. The results using CNN are better than expected. Naïve CNN architecture only requires 40 epochs to achieve convergent accuracy, which DNN architecture requires around 200 epochs to reach its peak accuracy. This model is somewhat underfitting, according to the author's analysis; this is due to the small data set.
For further analysis, the authors make a confusion matrix of the architecture that can be seen in Table 6.

Table 6: Confusion Matrix Arsitektur Naïve CNN

	Prediction				Recall (%)
	Class	1	2	3	
Facts	1	33	7	6	71.74
	2	6	36	6	75
	3	0	0	51	100
Precision (%)		84.615	83.72	80.95	

From Table 6, it is known that the architecture has an average precision of 91.30% and an average recall of 82.96%. When viewed from the average precision and recall models do not look good to use. Still, when seen from recall in class 3, this model is suitable for predicting damage to 4-story building structures because the most important thing is to detect damage to damaged buildings in anticipation of buildings, which collapsed due to damage to the building structure.

- VGG19

Next, the author will experiment using VGG19 architecture, as previously described. However, in this study, the authors changed the VGG19 architecture, which was initially a 2D CNN architecture; the authors altered the VGG19 to the 1D CNN version.

The accuracy using training data is 87.51%, while when using testing data is 82.76%. VGG19 results with CNN naïve did not differ much in terms of training and testing accuracy. Both CNN architectures are both underfit. CNN architects, especially VGG19, are indeed made to classify images in large numbers. Thus, there is inadequate data they do not work as effectively as they should, but with a difference of 5%, the average results of the experiments show the test data is still above 80 %. For further analysis, the authors make a confusion matrix of the architecture that can be seen in Table 7.

Table 7: Architecture of Confusion Matrix VGG19

	Prediction				Recall(%)
	Class	1	2	3	
Facts	1	43	1	0	97.73
	2	9	38	2	77.55
	3	9	2	41	78.85
Precision (%)		70.49	92.68	95.35	

From Table 7, it is known that architecture has an average precision of 83.09% and an average recall of 82.25%. If it is only seen from the average accuracy and recall, this model is good enough to be used, but when viewed from a third-class recall, this model is perfect to use. The model can predict damage to the 4-story building structure correctly. To help to conclude from experiments with the statistical features, the authors make the best accuracy comparisons of the DNN naïve architecture, CNN naïve, and VGG19 in Table 8.

Table 8: Comparison of Accuracy of Training and Testing Results from Naïve DNN Architecture, Naïve CNN, and VGG19 Using the Statistical Features

(%)	Naïve DNN	Naïve CNN	VGG19
Training Accuracy	85.90	87.20	87.51
Testing Accuracy	84.14	82.76	82.76
Rate of precision	86.17	91.30	83.09
Rate of recall	84.71	82.96	82.25

From the comparison shown in Table 8, it can be seen that the results of the DNN naïve architecture with 6 hidden layers are not too different from the results of the CNN-based architecture but if we look deeper, to achieve this accuracy DNN requires around 400 epochs but the naïve architecture of CNN and VGG19 only need 60 and 100 epoch. The vast difference from the number of epochs needed makes the results of CNN-based architecture better for use in predicting damage to a 4-story building structure.

For CNN-based architecture, which is better, if the writer only sees from the accuracy, it is challenging to determine because both have similar results even in the sample that I took this time; they both happen to have the same testing accuracy. If seen from the time needed for architecture to achieve convergent efficiency, CNN naïve architecture is narrowly won. Still, to make this decision, the writer must return to the purpose and background of this research, namely detecting damage to the 4-story building structure. To achieve that goal, the most important thing to look at is a recall in the 3rd class, and based on that comparison, the author can conclude in this study that VGG19 architecture is the best architecture that can be used to predict damage to a 4-story building.

4. CONCLUSION

From the experiments and analyzes conducted, it can be concluded from this research that:

1. The most fitting order to use by a Butterworth filter to make a bandpass filter is order 11.
2. The maximum and minimum statistical features cannot be used as the only reference feature.
3. The best number of hidden layers of naïve deep neural network architecture to answer the problem in this study is six hidden layers.
4. Convolutional neural network-based architecture is better than naïve deep neural network architecture in looking for features and predicting damage to 4-story building structures from statistical data.
5. VGG19 is the most suitable architecture to be used to answer the problems in this study, based on the faster time needed, recall of structural damage, and good predictive accuracy that is 82.76% .

Based on the research conducted, there are still limitations that exist in the study, then here are some suggestions for further research:

1. Increase the number of data sets per class, the large number of data sets is beneficial in this research model.
2. Take data sets from several different models so that the data variants will be better, this is very helpful so that the prediction model becomes fit.
3. If you have more data, do try other well-known CNN architectures such as residual neural networks, inception-v4, etc.
4. Try to do a type of research on other civil objects such as skyscrapers, aircraft wings, bridges, and so on.

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