Predicting Fault Proneness of Programs with CNN

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Abstract: There has been a lot of research aimed at improving the quality of software systems. Conventional methods do have the ability to evaluate the quality of software systems with regard to software metrics. (i.e. complexity, usability, modifiability, etc.) In this paper, we apply one of the deep learning techniques, CNN (Convolutional Neural Network), in order to infer the fault proneness of a program. The CNN approach consists of three steps: training, verification of the learning quality, and application. In the first step, in order to make training data, we transformed 27 program source codes into 1490 images with colored elements, so that the features of the images remain. In the second step, we set the goal of the accuracy of machine learning and trained with the training data. In the third step, we forced the trained system to infer the fault proneness of 692 images, which were transformed through 5 programs. This paper presents the effectiveness of our approach for improving the quality of software systems.

1 INTRODUCTION

Software systems have become deeply involved in our lives as social systems. As a result, systems are required to satisfy and excel better usability for diversified end users, safety, and security for our social life. Furthermore, architectural design for quick and flexible updating has become a common requirement. Flexible updating and/or responding means that the development period becomes shortened. Business owners also require that the developments be cost-effective. It is mandatory for developers to improve the productivity and efficiency of their developments, along with the quality of their products with regard to the tradeoff between the increasing requirements and the cost-effectiveness in time for delivery.

Researchers and developers developed various technologies to cope with human errors in analysis, design, and implementation. Finding and fixing these errors in the early stage of development is one of the important goals. In order to reduce the complexity of a given software, various system construction methodologies are also proposed. The most famous and influential one is the object-oriented software construction methodology (Mayer, 2000). Multi-agent systems also contribute to the ease of large scale software construction (Shehory and Sturm, 2016). Kambayashi and Takimoto (Kambayashi and Takimoto, 2005) demonstrated that multiple agents have introduced modularity, reconfigurability and extensibility to control systems, and simplified the development of such software systems. Even though the ongoing proposal of new methodologies are effective, the essential part of reliable software construction is in finding defects within the software. After all, software construction is reliant on human ability.

Practically, we know that we cannot fix all errors and defects through testing, and furthermore, some unknown defects sometimes cause fatal faults. We apply a CNN (Convolutional Neural Network) model to improve the quality of software. We call this system as a CNN based bug inference system (the CNN-BI system for short).

The purpose of this paper is to present the effectiveness of the CNN approach to predict the fault proneness of programs. CNN is one of the mechanisms of deep learning, has been successful in the field of image recognition, or inference as based on images. We expect the CNN-BI system to extract features of fault proneness of programs throughout the training, as the features of fault proneness of a program must be presented in the images. Furthermore, we expect the following effectiveness of the CNN approach.

- The source codes that cause fault must have peculiar features.
  The CNN approach may be able to find the features in the colored program images rather than in

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monochrome images.

- If the CNN model can infer the fault proneness of a program, we will be able to review and fix the program faults regardless of its completion.

Thus, we utilize source code images to train a CNN model in order to infer the fault proneness of programs.

The research questions of this paper are as follows:

- RQ1: Can a CNN extract features of fault proneness from images of programs?
- RQ2: If the CNN cannot infer fault proneness, what kinds of defects are missing?
- RQ3: Is the accuracy of the inference acceptable? How can accuracy be improved?

In order to get the answers to these research questions, we need to categorize elements of program source codes and transform programs into images that the CNN-BI system reads, which was carried out as follows. We transformed program source codes into images with colored elements to train the CNN-BI system. Since we did not have an acceptable number of training data sets, transfer learning (Weiss et al., 2016) was applied. Before the evaluation of the CNN, we train the CNN with images of fault prone and correct programs. Supervised learning was selected as the CNN's learning style, since the goal of inference was to conclude whether the program is fault prone or not. After the training, the CNN-BI system was evaluated as to whether the system could predict fault proneness of a program.

The remainder of this article is structured as follows. Section 2 presents related work. Section 3 describes a case study. In Section 4, we discuss the findings and their implications. Section 5 concludes.

2 RELATED WORK

There are a lot of methods that improve the quality of software. Techniques utilizing statistical methods are popularly applied, since the statistical approach can visualize the quality of software. If qualitative information can be presented quantitatively, we can compare the qualitative characteristics of programs with the quantitative data. We will be able to observe and control the quality of software quantitatively to improve the quality of software.

Cyclomatic complexity was introduced by McCabe in 1976 (McCabe, 1976). There is a strong correlation coefficient between the cyclomatic number and the number of defects. Therefore, when a program is measured with a big cyclomatic number, it implies that the program is more complex than programs with smaller cyclomatic numbers. The quantitatively presented "relatively complex" programs need to be carefully reviewed. After a decade, multiple paradigms began to be applied. For object-oriented software, Chidamber and Kemerer introduced metrics to measure complexity based on coupling and cohesion, readability, understandability, modifiability, etc. (Chidamber and Kemerer, 1994). Their set of metrics is known as *CK metrics*. Zimmermann also introduced a defect prediction model (Zimmermann et al., 2007). These methods are based on a quantitative approach to evaluate the quality of software systems.

The quantitative approach needs evaluation criteria. Lorenz and Kidd presented empirical data for typical metrics as criteria of the quality of object-oriented programs (Lorenz and Kidd, 1994). Their intention was that if the measurement of a program is not within the "normal" range, the program must be reviewed. This means that the metrics do not find defects or errors of programs. Furthermore, even though testing is effective in improving the quality of programs, it cannot discover all errors. One of the difficult points of improving the quality of programs is that all of the defects do not occur in the complex program. We employed another approach to decide which part to review intensively. The CNN approach may be able to find defects that occur not only by the complexity of the program, but also by the structural feature of the program.

After the *google cat* (Le et al., 2012), research and application examples of deep learning have increased. There are studies that have applied deep learning to software quality evaluation. For example, Morisaki applied deep learning to evaluate the readability of software in order to control the quality of software (Morisaki, 2018). Kondo et al. utilized deep learning to cope with the delay of feedback from static code analysis (Kondo et al., 2018). Yang et al. (Yang et al., 2015) also applied deep learning to observe software changes and proposed W-CNN rather than CNN. We evaluate the CNN-BI system whether it can predict fault proneness of programs.

3 CASE STUDY

In order to evaluate an inference of fault proneness of programs with deep learning, we analyzed the effectiveness of the inference qualitatively and quantitatively. In this section, we look at a case in which CNN has been applied in order to infer the fault proneness of programs. For training the CNN-BI system, we utilized TensorFlow and KERAS that are provided by Google with Python on Windows 10 Home. The development system configuration was Core i7 - 6700 K for CPU, 8 GB for MainMemory, and Geforce 980 Ti for GPU.

3.1 Overview

The case shown in this paper is a project with fifteen developers, who worked for a period of one year. The number of programs developed was 575. They used VisualBasic2008.

The images of programs were created by the following steps.

1. We collected source codes as training data.
   We randomly selected 27 programs from 575 programs.
2. Each element in the statements was color coded based on the following categories;
   - instruction: blue
   - reserved word: orange
   - comment: green
   - module name: bold face, green
   - global variable name: bold face, blue
   - local variable name: black
   - control name: pink
   - user defined function name, subroutine name: bold face, red
   - user defined type name: purple
   - string: brown
3. We divided each module program into subprograms with approximately thirty lines of code.
   "One function must be developed within thirty lines of code" is one of the coding conventions in the project.
4. The image of each subprogram was created in B5 size horizontals.
   We got 1490 images as training data. In other words, each image represents a program fragment. The fault proneness would be trained and inferred for each image.
5. The training data for supervised learning was categorized into two groups; "with fault" and "without fault," and were labeled "BUG" or "OK" respectively.
6. We trained the CNN-BI system with the training data.

   We used VGG 16 (VGG ILSVRC 16 layers) which is a learned model of ImageNet as the learning model of the CNN-BI system. The VGG16 has 16 layers in total, including 13 convolution layers, and 3 full connected layers. The VGG16 has learned about object recognition of 1000 categories.

   Figure 1 shows the structure of the VGG16. The convolution layers was reused as the learned models of the CNN-BI system. We trained the full connected layers with the training data in order to infer the fault proneness of program fragments, then classified them into two categories based on the presence or absence of defects, and output the inference results.

   Figure 2 shows the model of the all full connected layers that we trained. Such a learning method is called transfer learning. Transfer leaning helps us apply the trained model from a certain area to another area in which we have a limited amount of data. Hence, we utilized transfer learning and evaluate the quality of source codes with the limited amount of training data.
7. Similarly, we derived 322 images as verification data.
   Here, the verification data was utilized to verify the adequacy of the learning.
8. We verified the CNN-BI system with the verification data.
   Underfitting and overfitting were categorized as inadequate learning.

The amount of training and verification data is shown in Table 1.

Table 1: The amount of training data and verification data.

Data Category	Label	#cases
Training data	OK	945
	BUG	545
Verification data	OK	213
	BUG	109

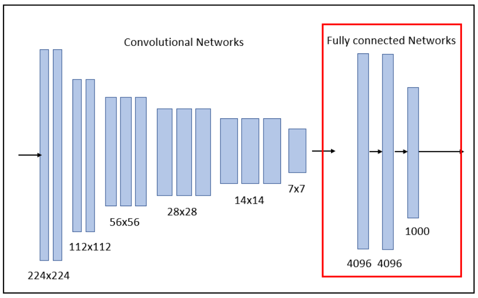


Figure 1: VGG 16 model diagram.

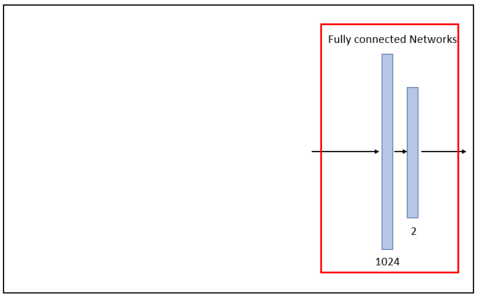


Figure 2: Modified model of the full connected layers.

3.2 Results of Training and Verification

We set the objective of the machine learning with the goal of achieving 85% of the accuracy. We weighted the training data (Japkowicz, 2000) so that the number of cases belonging to the two categories would be balanced. The training process with the learning data is shown in Figure 3.

The x axis and y axis of the figure shown on the left hand side represent the number of epochs, and the number of losses respectively. Similarly, the y axis of the figure shown on the right hand side represents the accuracy of the learning. Here, one "epoch" is one full training cycle of learning. Thus, x axis represents the number of training cycles. For example, 100 epochs mean that the machine learning cycle has iterated 100 times.

In the figures, the blue lines represent the loss and accuracy for training. On the other hand, red lines represent the loss and accuracy for validation. We have done 100 epochs of training. As shown in the Figure 3a, the loss drops to the right. Figure 3b represents the accuracy, and rises to the right. Because the lower loss and higher accuracy represents a better CNN model, the training was done successfully without overfitting nor underfitting. After the training, the loss and accuracy rates reached to 19.04% and 82.97% respectively.

The first goal of the accuracy of our training was 85% or greater. However, our achieved accuracy rate was 82.97%, which was lower than our targeted accuracy, but we do retrain the ability to train CNN without overfitting or underfitting. Hence, we decided to apply the trained CNN to infer the fault prone program fragments.

3.3 Results of Inference

Thus, we applied the trained CNN-BI system to infer the fault proneness of program fragments. Constraints of the inference were as follows.

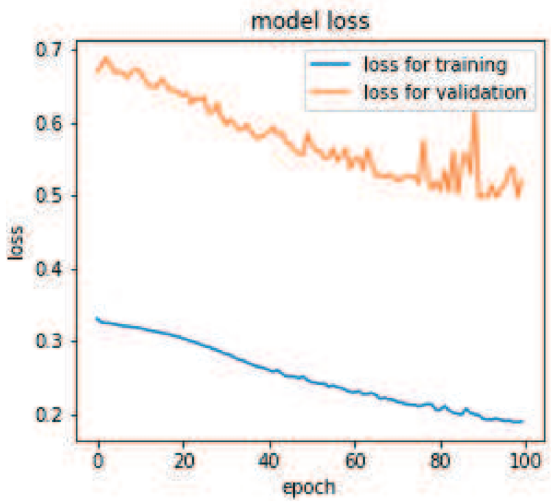
1. Source codes that were used to train the CNN-BI system should not be applied for the inference.
2. Source codes that we utilized for the inference should be programs that had not yet been corrected or modified to resolve the faults.
3. The number of "OK" and "BUG" images should not deviate considerably from the percentage of training data. This constraint was intended to make the inference result be comparable and verifiable with the training data.

The inference was carried out for 692 images. Then, we were able to get a judgement for each image. Figure 4 shows an example of the results of an inference. In Figure 4, the name of a jpeg file is shown at the top of the figure. The following image is the thumbnail of the inferred image. The inferred result is shown under the image. Since the training had been done with two labels: "OK" and "BUG", the label whose possibility is larger than that of the other label is shown as the inferred result. In this example, "Result: OK" represents that this program was *not* inferred as a fault prone program. On the other hand, if the result is shown as "Result: BUG", the image was inferred as a fault prone program. The bottom line of the figure represents the probability of BUG and that of OK. The results of the example are as follows, the probability of BUG was approximately 0.41, and that of OK was approximately 0.59.

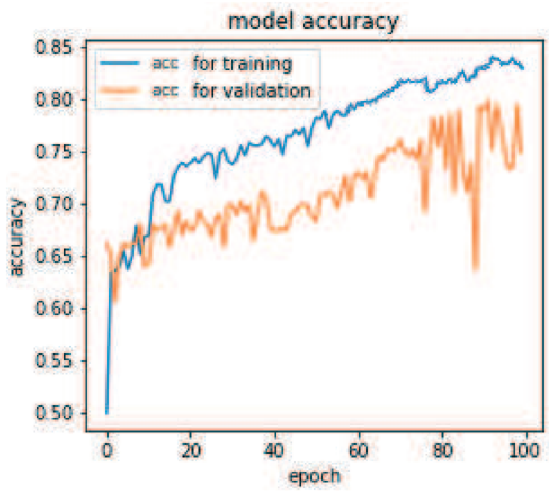
As we mentioned above, the inference data were program fragments before fixing any defects. In order to discuss the precision and recall to evaluate the results of the inferences, we investigated the modification history of the programs. If a program was not modified, the label of all of the images of the program must be "OK." Contrarily, if the program had been modified at least once, the labels of the images corresponded to the modified fragments of the program, and so, were "BUG", however, the labels of other images were "OK." If an inferred label was matched to the actual label, the result of the inference was correct.

Each program is plotted in Figure 5 with the number of images on the x axis and the number of defects on the y axis. As the number of images represents the size of a program, the inclination of the line that connects each plot from the origin represents the quality of the program. For example, if the slope is large, the quality of the program is low. There are two layered data in the figure. We categorized programs into three layers. Programs categorized in layer 1 were more fault prone than programs in layer 2.

In order to evaluate the inferred results, we examined precision and recall with the actual label of each program fragment. The inferred results are plotted in



(a) Epoch vs. Loss



(b) Epoch vs. Accuracy

Figure 3: Learning Process.

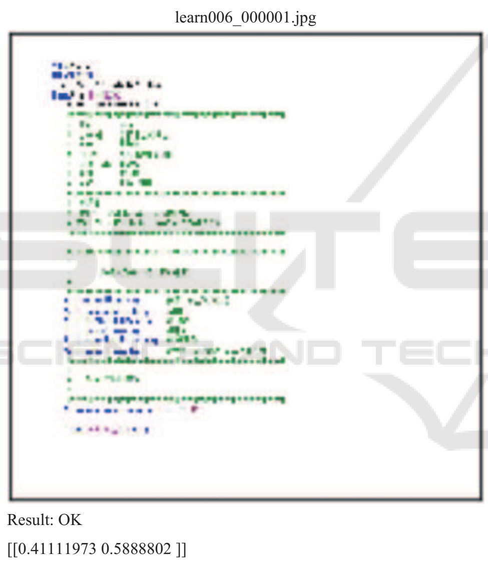


Figure 4: An example of the results of an inference.

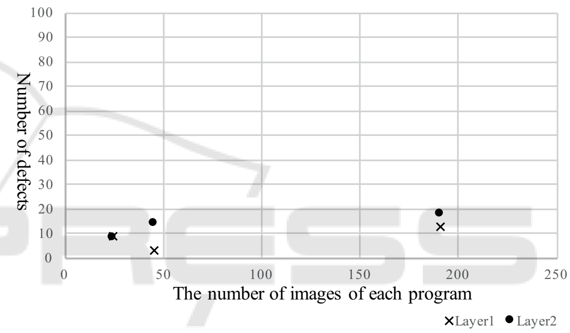


Figure 5: A scatter plot of the number of images derived from each program and the number of defects that were actually found in the program.

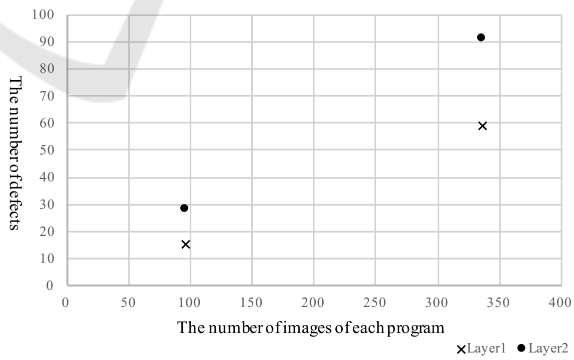


Figure 6: Scatter plot of the number of images and the number of inferred "BUG"s.

Figure 6 with the number of images on the x axis and the number of labels of "BUG" on the y axis.

Corresponding to the results of the label "BUG," we examine precision, recall, and F measure. Table 2 shows the results.

In Table 2, Pg. is the serial number assigned to the fragment of a program, while #Positive is the number of images that were inferred positively as the fault prone programs, and thus labeled images as "BUG." #True is the number of images that were actually modified fragments by fixing bugs.
#TP. is the number of images in which defects were detected or inferred correctly positive (true positive) by the actual debugging process and inference.

There were however, bugs that could not be deduced by the CNN. Table 3 shows the major defects that could not be deduced.

Images that include SQL statements were successfully deduced as fault prone programs. In general, syntax errors are detected by a compiler or a coding tool, but it is hard to detect errors in SQL statements

Table 2: Precision, recall, and F measure.

Pg.	#Positive	#True	#TP.	Precision	Recall	F
a	8	9	6	0.75	0.67	0.71
b	14	3	2	0.14	0.67	0.24
c	28	15	7	0.25	0.47	0.33
d	18	13	3	0.17	0.23	0.19
e	91	59	41	0.45	0.69	0.55

Table 3: The major defects that could not be deduced.

Pg.	Defects	#cases
a	Deletion of variables	1
a	Deletion of program codes	2
b	Correction of variables in the condition of an *IF* statement	1
c	Modification of called functions	8
d	Addition of program codes	4
d	Modification of program codes	3
d	Deletion of program codes	3
e	Addition and/or deletion of variables	13
e	Addition of program codes	1
e	Modification of program codes	2
e	Modification of called functions	2

Table 4: Precision, Recall and F measure of the result of interpretation of inference.

Pg.	#Positive	#True	#TP.	Precision	Recall	F
a	14	9	7	0.50	0.78	0.61
b	22	3	2	0.09	0.67	0.16
c	51	15	12	0.24	0.80	0.36
d	31	13	4	0.13	0.31	0.18
e	153	59	50	0.33	0.85	0.47

prior to the run time. The CNN was able to detect such defects that were sometimes hard to find. However, the inference of the CNN did not point out actual errors in the programs, but; the fault proneness of each image. Therefore, after the CNN inference, developers are expected to review the program fragments that are inferred as fault prone programs.

There are problems we shall solve. When we compared actual bugs with the inferred bugs, there were multiple cases in which the image was labeled with "BUG.".

Table 4 shows precision, recall, and F measure when we assumed that the CNN inferred the images subsequent to accurate images.

Because the number of missing defects had decreased, the recall had increased, that said, the precision and F measure had decreased. In order to improve precision, we should develop a method to create images from programs with regard to the logic or structure of the programs.

4 DISCUSSION

4.1 Possibility of Inference of Fault Prone Programs

In this paper, we applied images of programs into CNN in order to detect fault prone program fragments. The machine learning system learned the relationship between the fault and image based on the supervised learning. After the machine learning was completed, we analyzed the detected fault prone program fragments and evaluated the machine learning system.

4.1.1 Result of the Inference

Figure 5 and Figure 6 represent scatter plot with the number of images of each program and the number of actual/inferred faults. It means that the x-axis represents the size of each program and the y-axis represents their fault proneness. The scatter plot tells us that there was a strong positive correlation between the size of program and fault proneness. It is easy to interpret this phenomena, since the number of faults, as expected, increases according to the size of a program. As shown in the diagrams, the number of inferred faults was bigger than that of actual faults. This is not a problem, because if the inference can point out program fragments that need to be carefully reviewed, we will be able to improve the quality of software.

4.1.2 Inference of Faults

As shown in Table 2, the recall of the inferred faults was 0.68 at most. However, we now focus on faults in Table 3 and pick up faults that were not inferred by the machine learning system. The errors were as follows;

- Mistakes of variable names in conditional statements.
- Bugs in the addition and/or deletion of statements.

It must be difficult for any CNN based systems to detect such faults. These errors cannot be detected through inferences based on images. Even so, the CNN-BI system must still be useful. Bugs-prone program fragments with SQL statements were detected well.

The most important point of our research is that we clarify the weak points of the CNN-BI system when we apply the technique to improve the quality of programs. We will be able to review the weak points as well as the fault prone program fragments that are successfully inferred by the CNN-BI system.

4.2 Quality of the Inference

The precision, recall, and F-measure are shown in Table 4. Still now, we do not expect the CNN-BI system to infer with high precision, but, with high recall. It is important to gain greater recall than precision. According to our application of the CNN inference, recall is greater than precision for every project. In contrast, if precision is greater than recall, we may miss a lot of errors, and thus, and will not be able to improve the quality of software.

4.2.1 Improve the Accuracy of Inference

In order to increase the accuracy of the inference, we will collect a bigger training data set that will include various kinds of defects other than SQL statements. This is our future work.

4.2.2 Faults Inference with Images

Inferring defects in source codes by images of program fragments are effective in detecting defects in programs with SQL statements. The image of a program with SQL statements may have a typical feature. On the other hand, we found weakness in the CNN-BI system. Addition and deletion of variables and/or codes were not detected, since, these changes do not seem to cause any changes in the data of supervised learning.

The CNN-BI system's recall could be 85%. Though its precision was 33%, which is a result that implies the review of programs still needs a lot of effort on the part of reviewers, we can conclude that the inference with images for detecting fault prone program fragments works well. The following issues remain to infer the fault prone fragments of programs:

- Improve the precision of the CNN-BI system.
  In order to improve the precision, we need more training data, and we may have to re-consider the coloring rules. More or less colors may help the CNN-BI system improve the precision of its inference. When we convert a program fragment to an image, for example, we can change the size of characters. In our study, each program was divided into several images based on the number of lines of codes. There are other ways to divide each program; e.g. structural blocks, etc.
- Improve the scalability and applicability of the CNN-BI system.
  In this study, we utilized program source codes of a single project. We are not sure whether the CNN-BI system is scalable and applicable to other projects or not.

5 CONCLUSION

We have applied CNN with already trained data sets in order to infer fault prone parts of programs by transforming source codes to image data. The key of our approach is the way to derive images from the program source codes. We have taken advantages of the strength of CNN to extract features from image data.

We have demonstrated the effectiveness of our approach through the following processes.

- Analyze the inferred results as compared with the flaws that were actually found in target programs.
- Validate the result of inferred defects in the source code.

According to the results, we have succeeded in inferring fault prone parts of programs. Here are the answers to the research questions.

- The CNN-BI system could extracted features of fault proneness from images of programs. Even though the inference is not perfect, we can use our system to designate the focal points of program reviews. The CNN-BI system is effective to predetermine where we need to concentrate to investigate programs.
- We have successfully identified some typical flaws in programs. We also found that some categories of problems are hard to find with our approach.
- The accuracy of the inference acceptable was accepted in our study. We discussed the possible ways to improve the accuracy of the inference.

In the experiments, we have applied CNN to a small number of training data. In order to improve the accuracy of the inference, we need to train the CNN with a much larger collection of training data (programs).

In our future work, we need to expand our approach to grasp a much larger set of defects, which will contribute to the improvement of the quality of software.

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