Hybrid Probabilistic Deep Learning for Damage Identification

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ABSTRACT

In structural health monitoring, various types of sensors collect a large amount of data for structural defect detection. These data provide critical support for the application of machine learning for structural damage identification. However, machine learning relies heavily on training data, whose quality and distribution can affect the effectiveness of detection models in real-world damage identification. In addition, machine learning contains a large number of parameters that are highly uncertain, which results in the output of machine learning models is not always as reliable. These deterministic deep networks usually make overconfident decisions in some data. The ability of deep learning to provide safe and reliable decisions is very important when applied in the field of engineering. In order to ensure the decision security of machine learning models, this paper proposes a hybrid probabilistic deep network for structural damage identification. The proposed method converts deterministic weights into a Gaussian distribution, which in turn quantifies the uncertainty in machine learning. Among them, variational inference is used for uncertainty modeling of probabilistic deep networks. These uncertainty metrics can be used to determine whether the output of the machine learning model is reliable. Nevertheless, the introduction of uncertainty weakens the learning ability of deep networks. Meanwhile, the number of parameters in the probabilistic layer is twice that of the deterministic layer for the same architecture. Therefore, probabilistic deep learning is more difficult to train compared to deterministic deep learning. To address these issues, deep learning with hybrid probabilistic and non-probabilistic layers needs to be investigated. This paper analyzed and discussed the effects of different numbers of probability layers on the effectiveness of structural damage identification. Finally, a series of experimental results showed that the proposed method is able to accurately identify structural damage while quantifying the decision uncertainty.

KEYWORDS: probabilistic deep learning; damage identification; uncertainty quantification; variational inference

1. Introduction

Damage identification is one of the most important parts of structural health monitoring. Structural damage can affect the durability of structures. As the damage continues to develop, the increasing degree of damage may cause structural safety accidents. Therefore, it is essential to identify the structural damage. In recent years, there has been a rapid development of various types of devices with image collection capabilities. They can visualize the surface morphology of structures and provide richer sensory data for structural damage identification. These sensory data contain implicit properties of structural damage. Mining damage sensitive properties from these data is the first step in identifying damage. Recently, data-driven algorithms such as deep learning have gained much attention and achieved remarkable results in various fields. Structural damage recognition based on deep learning has also been rapidly developed [1]. Depending on the type of sensed data, the method can be divided into two categories. One category is oriented to one-dimensional temporal sensing data, such as acceleration and other structural responses. Zhang et al [2] proposed an incremental learnable machine learning method for identifying internal defects in wood in combination with ultrasonic signals. Compared with convolutional neural networks, their proposed method has the 12 times higher training efficiency and the 2.1 times higher inference efficiency. Liu et al. [3] used convolutional neural network to process the guided Lamb wave signal and thus achieve crack recognition in thin plate structures. The other category is oriented to two-dimensional sensing data, such as image data that can reflect structural phenotypes. Zhang et al. proposed [4] a surface crack recognition method based on incremental learning. Their method achieves the same level of recognition accuracy as the deep learning method, but the training efficiency is about 20 times higher than that of the latter. Moreover, the incremental learning mode is more in line with the practical engineering needs and can further reduce the update time of the model [5]. Beckman et al. [6] proposed a damage volume quantification method based on deep learning and depth cameras. The method can quantify the spall volume of multiple surfaces in concrete structures simultaneously. The average accuracy error of volume quantification is 9.45% when the distance between the structure and the depth camera is in the range of 100 cm to 250 cm.

Most of the existing deep learning methods are deterministic methods, which can only give deterministic recognition results. This type of approach tends to make some overconfident decisions. Bayesian is one of the main tools for quantifying uncertainty, and it has been widely used in civil engineering. Yuen et al [7] proposed a Bayesian nonparametric general regression with adaptive kernel bandwidth, which can adapt to non-uniformly distributed training data, and achieved significant results in modeling seismic attenuation relations. Luo et al [8] proposed an improved Bayesian damage identification method, established a new objective function based on autoregressive coefficients, and introduced particle swarm optimization to improve the standard Metropolis-Hastings. Combining Bayesian theory with deep learning methods will facilitate the development of deep learning in uncertainty quantification and better evaluate the processing of deep learning models for different distributions of perceptual data. In this paper, a hybrid probabilistic deep learning method is proposed for structural surface crack identification. Compared with ordinary deep learning methods, this method not only enables highly accurate damage recognition, but also quantifies the uncertainty of decision making. Meanwhile, uncertainty is one of the key indicators of the generalizability of the model. Section 2 shows the core theory of hybrid probabilistic deep learning. Section 3 shows and analyses the recognition effects of hybrid probabilistic deep learning models in the crack classification task. Section 4 summarizes the entire article.

2. Probabilistic Deep Learning

Probabilistic deep learning combines Bayesian theory with deep neural network methods and introduces uncertainty of parameters into deep learning models, making it possible to have quantitative decision uncertainty. Quantifying uncertainty can help deep learning models escape the problem of overconfidence. Therefore, a probabilistic deep learning-based crack identification method is proposed in this paper. Compared with ordinary deep learning methods, the proposed method uses the probabilistic layer to introduce uncertainty in the parameters. In this paper, we mainly focus on two-dimensional damage images as the processing object, so the two-dimensional probabilistic convolutional layer is the core component of the proposed probabilistic deep learning. Further, in order to improve the recognition accuracy of probabilistic deep learning, probabilistic convolutional layers and ordinary convolutional layers are used together. For the normal convolution layer, the input is convolved with the convolution kernel for the convolution operation. The ordinary convolutional layer obtains deterministic weights by point estimation. However, the weights and biases in the probabilistic convolution layer are derived from a distribution. If the posterior distribution of the parameters in the network can be obtained, the uncertainty of the weights can be taken into account. The posterior distribution of the parameters is calculated as follows:

$$p(w \mid D) = \frac{p(D \mid w)\, p(w)}{p(D)} \tag{1}$$

where $p(w|D)$ is the posterior distribution of the parameters; $p(w)$ is the prior distribution of the parameters; $p(D)$ is the evidence; $p(D|w)$ is the data likelihood. However, it is very difficult to compute the posterior distribution directly, and variational inference is generally used to update the probability model. It uses the variational distribution to approximate the true posterior distribution. It uses the variational distribution to approximate the true posterior distribution and updates the parameters in the network by minimizing the Kullback-Leibler Divergence (KLD) between the variational distribution and the prior distribution. The objective function can be approximated by Monte Carlo as:

$$Cost(D,\theta) \approx \frac{1}{N}\sum_{i=1}^{N}[\log q(w^i \mid \theta) - \log p(w^i) - \log p(D \mid w^i)] \tag{2}$$

where w^i denotes the i-th Monte Carlo sampling according to the variational posterior $q(w^i|\theta)$. In this paper, the variational posterior uses a Gaussian distribution, which is denoted as $\theta = (\mu, \sigma)$. μ denotes the mean of the distribution and σ is the standard deviation of the distribution. For the weights w in the network, we use their distribution parameterization to represent them. Therefore, the number of parameters in the probabilistic layer is twice as many as in the non-probabilistic layer. The training process of a neural network consists of forward computation and backward transfer. In the forward calculation, the parameter values in the probability layer are drawn from the variational distribution. This part requires the use of reparameterization. ε is obtained by sampling from the parameter-free distribution (N(0, I)). The weights w obtained from the sampling are:

$$w = \mu + (\log(1+e^{\sigma})) \times \varepsilon \tag{3}$$

where the distribution of weights is (μ, σ). Bayes by Backprop can be compatible with the backpropagation algorithm to learn the probability distribution of the neural network weights [9]. This form of updating parameters is similar to that of ordinary non-probabilistic neural networks and provides the basis for hybrid probabilistic deep learning networks.

3. Probabilistic identification of crack damage

3.1 Crack image dataset

In this paper, a crack damage classification dataset consisting of 2600 images of size 128×128 pixels is used [10]. Of these, 1300 images contained cracks and the other 1300 images did not contain cracks. 80% of the images are randomly selected as the training and validation set for the probabilistic model, and the remaining 20% images are used as the test set. Some image samples in the dataset are shown in Figure 1.

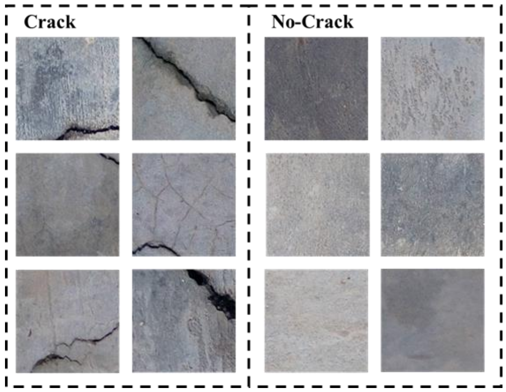


Figure 1. Some image samples.

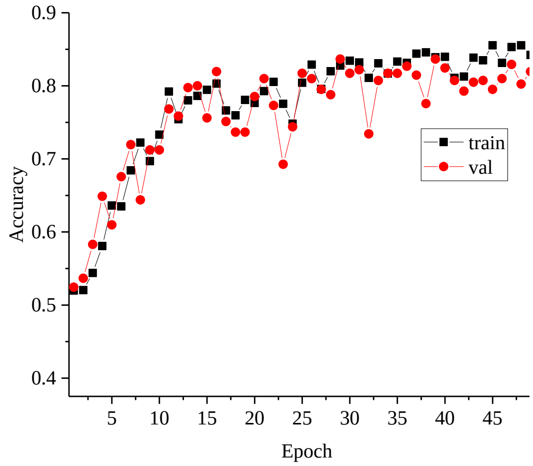
3.2 Hybrid probabilistic deep model

Compared to the convolutional layer, the probabilistic convolutional layer has twice the number of parameters. As a result, probabilistic convolution is more difficult to converge. To improve the recognition accuracy and effectiveness of detection models, hybrid probabilistic deep learning networks are designed. In this section, four hybrid probabilistic deep learning architectures are used, employing 1 probabilistic convolutional layer and 1 convolutional layer (model-11); 1 probabilistic convolutional layer and 3 convolutional layers (model-13); 2 probabilistic convolutional layers and 2 convolutional layers (model-22); and 3 probabilistic convolutional layers and 1 convolutional layer (model-31), respectively. The training process of the four hybrid probabilistic deep learning networks is shown in Figure 2. When the total number of both convolutional and probabilistic convolutional layers is 4, the more the number of convolutional layers, the faster the model converges. When the number of probabilistic convolutional layers is 3 and the number of convolutional layers is 1, the recognition accuracy of the detection model is significantly lower than that of other hybrid probabilistic detection models. The performance of each hybrid probabilistic detection model is shown in Table I. It can be seen from this that the more the number of convolutional layers, the higher the recognition accuracy. Therefore, combining the probabilistic and non-probabilistic layers can effectively improve the recognition accuracy and training efficiency of the model.

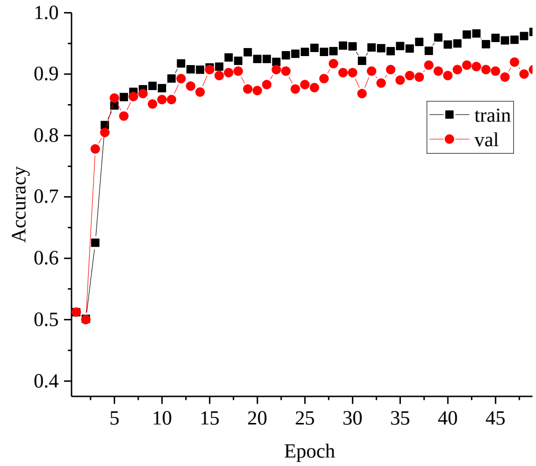
TABLE I. RECOGNITION PERFORMANCE OF DIFFERENT HYBRID PROBABILITY MODELS

Model	Training accuracy	Validation accuracy	Testing accuracy
model-11	0.8452	0.8024	0.8154
model-13	0.9645	0.9244	0.9365
model-22	0.9361	0.9049	0.9173
model-31	0.8590	0.8439	0.8596

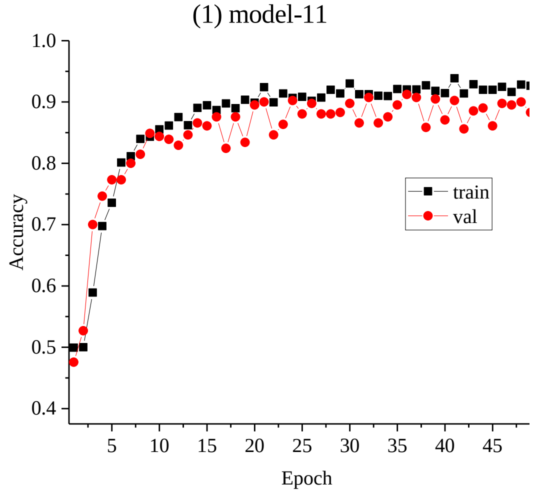
Two of the hybrid probabilistic models are selected for the uncertainty quantification analysis, i.e., model-11 with one probabilistic convolutional layer and one convolutional layer and model-13 with one probabilistic convolutional layer and three convolutional layers. These models are used to identify three representative sample images, as shown in Figure 3.



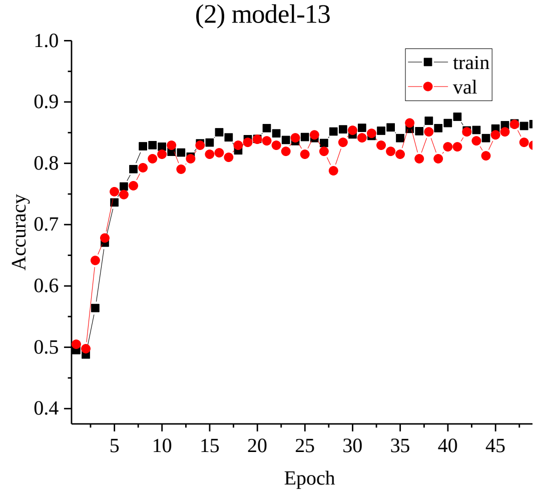
(1) model-11



(2) model-13



(3) model-22



(4) model-31

Figure 2. Training process of hybrid probability models.

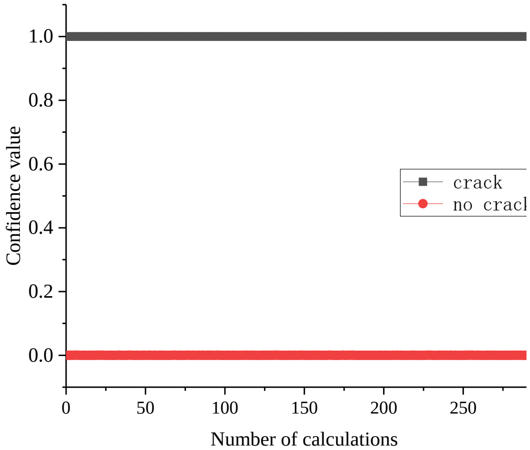
a

b

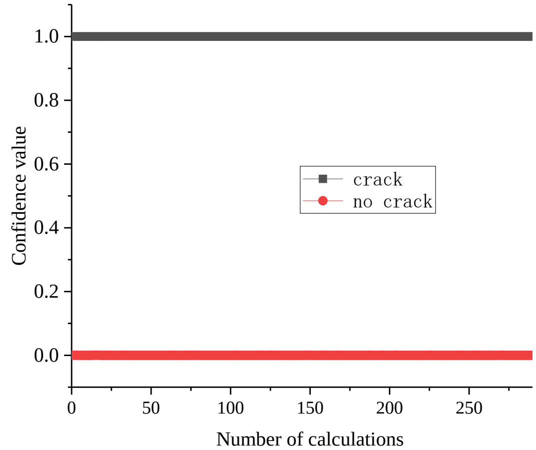
c

Figure 3. Samples for uncertainty analysis.

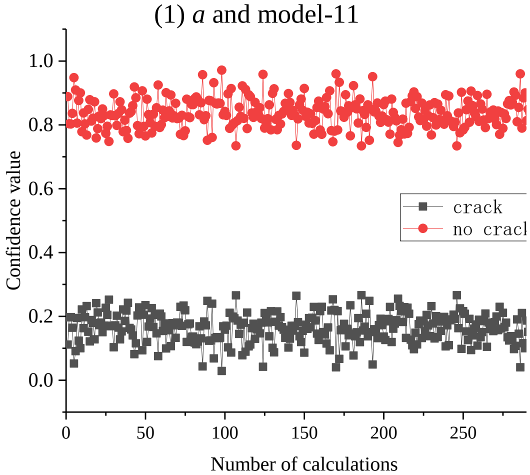
As can be seen in Figure 4, both hybrid probabilistic deep learning detection models achieve accurate recognition of crack image with very small uncertainty. In addition, model-13 also achieves accurate recognition of no crack image with very small uncertainty. The uncertainty quantification for decision making with hybrid probability models is shown in Table II. However, for the no crack image containing small stones, model-13 incorrectly determines them as cracks with a small uncertainty. By comparison, it is found that when the recognition accuracy of the probabilistic model is higher, its uncertainty is lower.



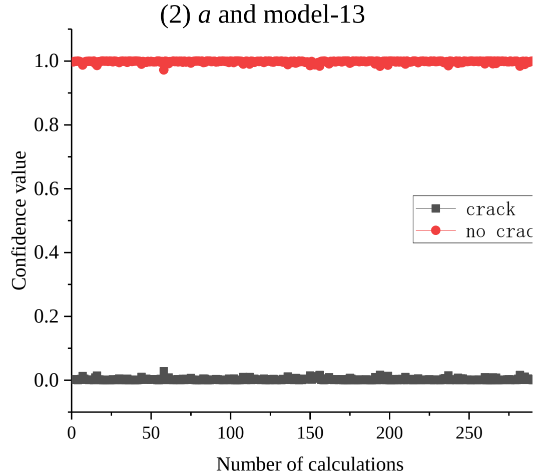
(1) *a* and model-11



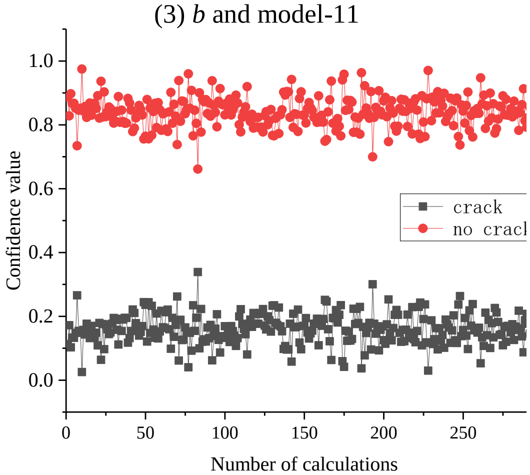
(2) *a* and model-13



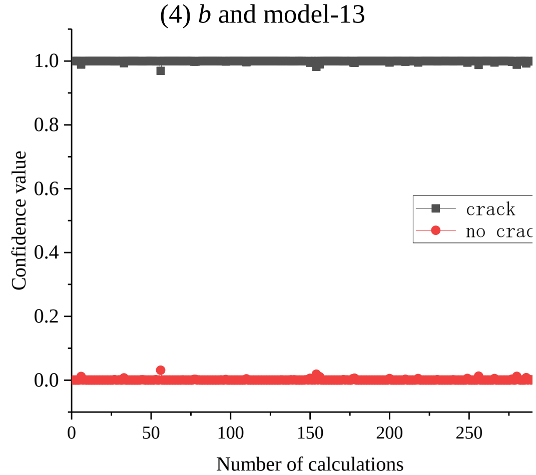
(3) *b* and model-11



(4) *b* and model-13



(5) *c* and model-11



(6) c and model-13

Figure 4. 300 recognition results of different hybrid probability models for the three samples.

TABLE II. UNCERTAINTY QUANTIFICATION FOR DECISION MAKING WITH HYBRID PROBABILITY MODELS

Model	***a***	***b***	***c***
model-11	0.0001	0.3601	0.3645

model-13	$5.5e^{-6}$	0.0637	0.0191

4. Conclusion

This paper presents a probabilistic deep learning method for structural surface crack recognition. The proposed method can quantify the uncertainty of decisions and prevent overconfident decisions. This paper compares and analyses in detail the effect of the number of probability layers on the recognition effect and uncertainty quantification results. The more the number of probabilistic convolutional layers, the better the ability of probabilistic deep learning to extract features, but a bottleneck also occurs. In addition, to further improve the recognition of probabilistic deep learning, the probabilistic convolutional layer is used together with the ordinary convolutional layer to estimate the output of the network and its uncertainty. A series of comparative results showed that convolutional layers can facilitate fast convergence of probabilistic models and further improve the recognition accuracy of probabilistic models. In addition, the higher the recognition accuracy of a probabilistic model, the lower the value of its quantified uncertainty. Therefore, probabilistic deep learning has a large potential in the field of engineering safety detection.

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