Machine Learning and Convolutional Neural Networks – Systems Based on Identification of Silicon Carbide Defects

Lei Zhang

Communication technology, Hangzhou Dianzi University, 310018 Hangzhou, China
burgermer@ldy.edu.rs

Abstract. Silicon carbide, which is a material we all call third-generation semiconductors, has special potential in 5G base stations and new energy vehicle charging. To make a better quality silicon carbide crystal, the key is to find out what defects it has. But now the factory mainly relies on manual inspection of these defects, this method is not reliable, often in the case of inequality or leakage.Better yet, we combine the method of the model that has been trained with incremental training, which can make the model more accurate and stable. Experiments have found that this method is particularly good, especially when classifying crystal defects, and even those small structural problems can be found. This method should be of great use in the fields of semiconductor production and optoelectronics. If the factory can use this automatic detection system, it can greatly improve the detection speed, reduce the error caused by manual operation, and reduce the production cost.It will be particularly easy to use in production, both flexible and accurate.

Keywords: Silicon carbide crystals, Crystal defect detection, Cconvolutional neural networks (CNN), Machine learning (ML), Pre-trained model architecture.

1 Introduction

Now 5G communication and new energy vehicles are used in the high-tech field of many high-end semiconductor materials, of which the third-generation semiconductor material silicon carbide (SiC) is particularly popular. SiC crystals are very suitable for high-power electronic devices, mainly because it has several very good advantages, such as being able to withstand strong electric fields, good thermal conductivity, and fast electronic movement. However, when SiC crystals grow, there are always some defects, such as thread screw detachment TSD and thread edge destation. In severe cases, the device can even be broken directly. So in order to improve the quality of SiC crystals and make the production of semiconductor devices smoother, the key is to find

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these defects quickly and accurately. Previously, detecting defects mainly by manual inspection or manually extracting features using machine learning algorithms, but manual inspection is too time-consuming and error-prone, and manual methods for extracting features are particularly susceptible to environmental impact, and cannot handle large-scale detection tasks [1, 2].

This paper mainly wants to better identify defects in SiC crystals by adjusting machine learning algorithms and improving the structure of convolutional neural networks to make the whole process more automated. What we are particularly concerned about is how to make the model perform more stable in the face of data imbalance, while improving the accuracy of identification of different types of defects, such as TSD, TED, and MP, and to reduce the misjudgment and leakage.

2 Relevant work

Now, when studying the identification of silicon carbide crystal defects, we generally still use the old method, that is, by manual inspection or manual extraction of features. But these methods are not very good, the efficiency is relatively low, and the accuracy is not high enough. In recent years, the development of deep learning technology has been particularly fast, especially the convolutional neural network, which has gradually become the most commonly used method in defect recognition [3-5].

2.1 Traditional methods for SiC crystal defect identification

In the past, there were two main methods for identifying defects, one was done, one was done, and the other was machine-learning, and the other was machine learning, which required manual definition of features. Although artificial inspection looked simply, it was a lot of problems. Especially when the crystal became larger, this method usually took a lot of time and effort. Some people use techniques such as local binary mode or directional gradient histograms to extract surface features [3]. But one problem with these methods is that they need to manually set a feature window for each image. Doing so will produce a lot of repetitive work and is particularly sensitive to environmental factors such as changes in light and background changes.

2.2 Application of convolutional neural networks (CNN) in defect recognition

Convolutional neural networks, which we often call CNNs, are particularly powerful in image processing because they can learn many useful features on their own. Many works on image classification and object recognition now uses CNNs. In the field of detecting SiC crystal defects, CNNs have the advantage of being able to extract different levels of features directly from the original image. The advantage of this is that they don't have to manually design features like traditional methods, save a lot of trouble, and perform more accurate and stable in practical applications. This model is powerful enough to accurately identify structural defects caused by temperature changes, external pollution, or equipment problems. From the experimental results, CNNs can indeed distinguish between different types of defects. Compared with previous methods that require manual detection, CNNs are more accurate and faster. The most powerful aspect of this research is that it gives full play to the characteristic extraction capabilities of CNNs and realizes the automatic identification of structural defects in complex contexts.

However, in 2023, Shi's team came up with a new network model called SCDD-Net [4], which is designed to examine the various defects in the SiC crystals, because the structure of the SiC crystal itself is relatively special. They added two things to the network, the space pyramid pool module and the global context module, so that they can combine the characteristics of different sizes well together. The advantage of this is that the test results are more accurate and the speed is much faster. Although many people used CNNs to identify SiC crystal defects, the effect is indeed good, but the existing methods generally have several problems, such as the model adaptability is not strong enough, small target recognition is not good, too dependent on training data[5, 6]. To solve these problems, you can start by improving the network structure, trying to better integrate the characteristics of different scales, and collect a variety of data samples.

2.3 Deep Learning-based defect detection technology

In recent years, deep learning has developed particularly rapidly, and has entered a more advanced stage, and now a lot of research is trying to use deep learning models to make defect recognition more accurate and faster. The most familiar is probably the convolutional neural network CNN, but there are many other deep learning models that are also very useful, such as the deep residual network ResNet and the generative adversarial network GAN have been used to detect defects[1, 5].The GAN network is also interesting, and it has been used in many studies to be used for defect detection, especially when it is used to increase training data. GANs work on the principle of two networks competing with each other, so that they can generate particularly realistic images. This feature is particularly useful, because many times we train models with insufficient data, and GANs can solve this problem and make models learn better.

In recent years, in addition to the deep learning methods that everyone is using convolutional neural networks and generative adversarial networks, many researchers have also begun to pay attention to combining traditional machine learning and deep learning, so that the effect of defect recognition can be better. Some studies mainly use convolutional neural networks to extract features that are particularly good at extracting features, first using them to extract high-dimensional features in images and then sending these features to support vector machines or random forests. The characteristic diagram of the surface defects of the railway was used to classify the support vector machine, and it was found that in complex scenarios, this hybrid method was more accurate than the recognition accuracy of the convolutional neural network or the support vector machine alone [7]. Ding's group also did similar work, improving the structure of the convolutional neural network to extract the defects on the printed circuit board, and then combining the random forest classifier, which greatly improved the detection accuracy and generalization ability of the small defects [8]. Combining the two methods at the characteristic level is indeed a good way to improve the effect of industrial defect recognition. When it comes to silicon carbide crystal defect identification, the use of deep learning, especially convolutional neural networks, has a particularly good future, because these models can automatically extract features, and can also process a large number of image data in complex environments, so that defect detection is fast and accurate [9]. I believe that with the continuous improvement of algorithms and the richness of data sets, the defect recognition technology based on deep learning will definitely play an increasingly important role in the production process of silicon carbide crystals.

Although there have been many researches devoted to crystal defect recognition using deep learning techniques, how to improve the generalization ability of the model, deal with unbalanced data, and how to achieve real-time detection in real production are still challenges to be solved in practical industrial applications.

3 CNNML method

The main purpose of this paper is that we have developed an optical detection system developed to identify silicon carbide crystal defects. The system mainly uses convolutional neural networks and machine learning techniques, which can automatically examine the image of the surface of silicon carbide crystals and can accurately identify different types of defects. In order to make the system more accurate and stable, we have tried a gradual learning method and also used pre-trained models.

3.1 Dataset construction and preprocessing

To achieve efficient and accurate defect identification, the study initially had to build a database of images containing various SiC crystal defects. The database consists of a large number of SiC crystal images obtained in different situations and with images with pervasive defects such as growth changes, particle impacts, and node slicing.

This study takes into account that the type and distribution of defects in the picture vary greatly, so the data-enhanced method helps the model train better, while avoiding the model from being too rigid. The specific approach is to do some random processing of the original picture, such as turning the picture angle, flipping it around, zooming in, or intercepting some of it, which can make the training of the picture more diverse [1, 3].

First of all, we have to find the original pictures of the original SiC crystals from the database. After getting these pictures, in order to make the model better, we will make some changes to these pictures, such as randomly rotating, flipping, cropping part, or adjusting the color, so that we can get more different pictures. After these processing, the pixel value of the picture is adjusted to 0 to 1, so that the processing is to make the training process faster and the model can be better. The effect. This separation can make the training process more stable, and the trained model can better adapt to the new data.

3.2 Convolutional neural network (CNN) model design

This study mainly used several more common convolutional neural network models, including the classic network structures of LeNet-5, VGG-16, and ResNet-18. To make these models perform better during the training process, we used incremental learning methods to train them, which can improve the accuracy of recognition and make the training process more stable [5].

LeNet-5 is arguably one of the earliest models of convolutional neural networks, and it makes important contributions to the specific problem of image classification. The structure of this network is not very complex, consisting mainly of two convolutional layers and two pooled layers, and finally two fully connected layers. Although it seems simple, it has laid a good foundation for the later development of deep learning.

The network's biggest feature is that it uses a lot of 3x3 small convolutional cores, which are stacked one by one, so that more complex features can be extracted from the images. Our research mainly uses VGG-16 to deal with images of SiC crystal defects, which are more complex.

The network model ResNet-18 uses the design idea of a deep residual network. This design has a great advantage, that is, it can handle the common gradient disappearance problem in deep neural networks, mainly by the structure of the remaining connections in it. ResNet-18 has a particularly powerful point, that is, it allows the ultra-deep network to train well, and there will be no common overfitting phenomena.

3.3 Model evaluation and performance validation

The paper mainly wanted to see if the model was good or not, so we did a lot of testing to evaluate its performance. We used a 50% cross-validation method, which is to divide the data into five parts, one of which was tested each time, and the remaining four were used for training, so that the take turns being tested five times. The advantage of this is that we can check the performance of the model more comprehensively.

4 Discussion

4.1 Advantages of the method

The paper focuses on the silicon carbide crystal defect recognition system, which uses convolutional neural networks and incremental learning methods, mainly to make defect detection more accurate and faster. With deep learning models, especially CNNs, some of the problems of traditional methods can be solved. One of the benefits of CNN is that it can find complex features from the picture on its own, without the need for manual feature extraction methods as before.

4.2 Application prospects and future research

Application prospects. This paper mainly examines the identification of SiC crystal defects, which can be used in many places, especially in the popular fields of semiconductors, opton electronics, and new energy. SiC materials are often used in particularly harsh environments, such as high power, high temperature or high frequency, so it becomes particularly important to accurately identify defects in materials. If factories can use automated defect recognition systems, they can improve production efficiency, reduce the mistakes that are easy to make manual inspection, and save a lot of production costs. If this technology can be used on a large scale in the factory, the company can save a lot of labor costs, and the quality of the product can be guaranteed. Later research can also use this method with other detection methods, such as X-ray imaging [8, 10] , infrared imaging, or ultrasonic detection, so that the inspection will be more comprehensive and accurate.

Future research directions. In terms of data, we need to prepare more samples of different types of SiC crystal defects, and we need to label these data more carefully so that the model can be better trained. For the model itself, you can try to use some simpler network structure or find ways to make the model smaller and faster, so that it is not too slow when actually detecting. Another important point is to make the model easier to understand, and we can study how to make the deep learning model less like a black box or directly use some of the algorithms that are better explained in themselves, so that the technicians in the factory can understand how to make the model. Use these different sources of information together, so that the SiC crystal defect detection will be more comprehensive and accurate, and the final product quality will be more secure.

5 Conclusion

The main thing we did was to make the process of detecting silicon carbide crystal defects more accurate and stable. To do this, we first collected a lot of pictures of silicon carbide crystals, which contained different types of defects. Then we used several common convolutional neural network models, such as LeNet-5, VGG-16, and NetRes-18 to train the system to automatically identify crystal defects. Another benefit of incremental learning is that it can slowly make the system better as more data is collected. With this method, the whole system will be more flexible and reliable. We have done a lot of experiments to test the system, using 50% cross-validation and some commonly used evaluation indicators, such as accuracy, accuracy, recall rate, and F1 score, which proves that this method is indeed quite good.

Although this research has not yet yielded particularly good results, the research direction to be done is still very important. Now the data set is not large enough, the variety is not enough, if you can expand the amount of data to collect different types of defective samples, so that the trained model can better adapt to various situations, the accuracy will be higher. Now there is a big question that the deep learning model needs a lot of computing resources when processing big data. If the explanation can be better, the people in the factory can more clearly know what is going on in the production process, and then adjust it in time. In the future, the physical data of temperature and pressure can also be added to the inspection system, so that the multi-faceted data will be combined to make the judgment of defects more comprehensive. Because silicon carbide crystals are used in semiconductor, optoelectronic and energy industries, so this method may also be used in the future to detect defects in other materials, especially in those where the accuracy and reliability requirements are particularly high.

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