Forgery Detection in Medical Images: A Case of Covid-19 using Convolutional Neural Network

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***Abstract*— Detecting medical data tampering has emerged as a major challenge in the processing of medical data that is secure-aware. Recently, there has been a growth in the illegal practice of misrepresenting healthy persons in medical records as Covid-19 sufferers. This poses a threat to the integrity of the data, making forgery detection critical. Convolutional neural networks (CNNs) have proven to be effective in detecting anomalies in manipulated data by identifying distortion or tampering in the original data. In order to check the noise pattern in the data, this research uses a CNN-based error level analysis (ELA) approach to detect COVID-19 medical data forgeries. Through the use of data splicing forgery, sigmoid, and ReLU phenomenon methods, the suggested improved ELA method is assessed. Various types of forgeries are applied to COVID-19 data, and the proposed CNN model is then used to detect data tampering, achieving an accuracy of approximately 92%. Clinicians and the AI community are both interested in deploying artificial neural networks in early COVID-19 patient screening for speedy diagnosis as a result of this.**

Keywords—CNN, covid-19, Machine Learning, forgery detection.

I. INTRODUCTION

Forgery or manipulation involves altering the originality of an element, entity, or data, which has become more prevalent with the advancement of digital data processing. Subtle forgery methods have undermined the credibility and accuracy of digital photographs [1]. As a result, efforts have been made to develop new methods to combat multiple attacks for data forgery. The photograph tampering dates back to the early 1840s, and digital data tampering emerged in the late 20th century with the availability of low-cost software for easy modification of digital images. Verifying the accuracy of available digital content is essential since new software tools are being introduced to edit images and photographs as the use of digital data grows. Since digital photographs are utilized in so many different contexts, such as in newspapers, publications, the medical industry, and courts of law, it is crucial to protect their integrity [2-4]. There are active and passive methods for modifying medical data, with passive methods like data retouching, copy moving, and data splicing posing a significant issue in the field of digital data processing. To locate tampering, passive approaches analyze a raw image using various semantics and statistics. Picture forensic is an evolving field that aims to ensure digital image quality and reliability testing. Fig. 1 presents a taxonomy of picture editing techniques.

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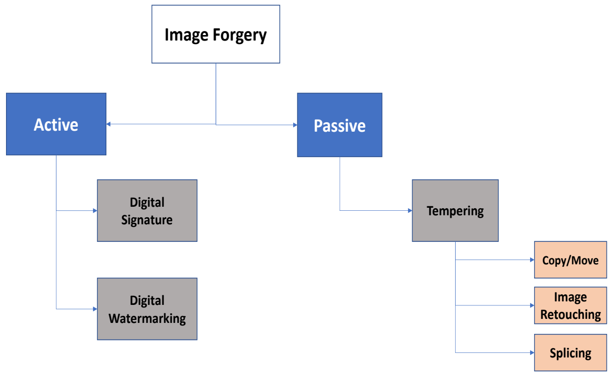

Figure 1: Shows the image Forgery techniques and its classification

Digital images have been altered using passive approaches, such as Copy Move, Image Splicing, and Image Retouching, in the field of telemedicine, which is a crucial one that needs the highest care and security. With the ability to send medical images via the internet [5] to aid in medical diagnosis and treatment, telemedicine has become more and more common. However, the widespread use of the internet has made medical image tampering a significant challenge for the industry. Medical images can be manipulated during transmission and misinterpreted by medical professionals if their integrity is compromised. Medical data forgery is not easily detectable by the human naked eye. The most popular way for altering the original image is copy move, while Image Splicing and Image Retouching are additional often used techniques for working with digital photos. Detecting retouching is particularly challenging, as there are usually no significant changes to the image. Lighting is often applied to spliced images [6], which makes it difficult for the forged image to match the exact lighting conditions of the original image.

Various classification methods have been utilized to identify forgeries in digital images, such as SVM, LS-SVM, and CNNs. The SVM classifier is akin to neural networks and evaluates textures and pixels of images to detect forgeries. LS-SVM is a supervised learning method that is useful [7] for classification and regression analysis. CNNs are versatile and have applications in video recognition, language processing, and recommending systems. They can also be used to evaluate forgeries in medical images that are not apparent to the naked eye. In this work, CNNs are used in combination with ELA to detect manipulated images. Whenever an image is edited, spliced, or watermarked, a noise pattern is introduced, which can be observed in the image's noise chart. An unknown image's noise attributes are first extracted using the suggested approach, and these attributes are then sent to the CNN classifier, which examines the noise pattern to evaluate whether the image has been altered.

We have proposed a novel method based on CNN for detecting forgery in COVID-19 medical X-ray images. This method utilizes an error level analysis (ELA) approach to assess the data for anomalies. In comparison to existing methods, including techniques involving data splicing forgery, sigmoid, and ReLU phenomenon methods, our approach demonstrates superior performance. Through rigorous evaluation with various types of forgeries applied to COVID-19 data, our CNN-based model achieves an impressive accuracy rate of approximately 92%. This advancement is of significant interest to clinicians and the AI community alike, suggesting potential deployment of artificial neural networks for expedited COVID-19 patient screening and diagnosis.

This is how the rest of the paper is organized. There is related work in section 2. Section 3 describes the actions of the proposed system. In section 4, the research findings are given. Section 5 concludes the paper.

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II. RELATED WORK

Splice forgeries, in-painting, copy-move forgeries, and image-wise adjustment are just a few of the methods that researchers have devised to spot tampering and pinpoint the damaged area in medical photographs. A suggested technique makes use of the Scale Invariant Feature Transform (SIFT) as a classifier to identify tampered regions and the local binary pattern rotational invariant (LBPROT) to extract important locations in medical pictures. An additional suggested technique divides a medical image into regions of interest (ROI) and not-interest (RONI), then use watermarking and the integer wavelet transform (IWT) to recognize and restore each region.

A forensic scheme that uses complex-valued convolutional neural networks (CV-CNN) to detect contextual abnormalities was also proposed, which was able to identify forgeries in medical watermarked images. In a [8] real-time application for monitoring children's activities, CNN was used to classify ten physical activities with an overall accuracy of 81.2%, outperforming the SVM. An octagonal block was employed in a block-based and key point discrete cosine transformation (DCT) method to decrease the number of matching features and increase the recovery rate of quantified DCT coefficients.

Rukundo Prince et al.[9] have proposed a method for addressing the urgent need for efficient detection of COVID-19, a disease responsible for a contagious respiratory ailment that has caused widespread fatalities and infections, affecting millions globally. The development of a computer-based tool that is fast, precise, and cost-effective is crucial in combating this pandemic. Recent research has demonstrated how well deep learning and machine learning models can identify COVID-19 from chest X-ray (CXR) pictures.

However, these models are hampered by notable limitations, including the necessity for extensive training data, larger feature vector sizes, a high number of trainable parameters, dependency on expensive computational resources such as GPUs, and extended run-times.

In response to the novel coronavirus variant's rapid spread during the recent pandemic, which has made it difficult to distinguish between the symptoms of ordinary colds and other respiratory disorders and coronavirus infections, another researcher [10] has developed a technique. The two most popular and effective ways to stop the transmission of infectious diseases are thoracic X-rays and Polymerase Chain Reaction with Reverse Transcription (RT-PCR). Machine Learning (ML) algorithms have become widely used to assist in the diagnosis of medical pictures in recent years, providing faster, more accurate, and more straight forward results.

The purpose of this work is to extract features from X-rays of the lungs of COVID-19 patients using texture descriptors, and then apply those features to frameworks created especially for the proper assessment of COVID-19 patients. To incorporate these new features into the suggested models, a number of experiments have been carried out using both individual texture descriptors and their integration. These frameworks will also be contrasted with traditional machine learning models that are commonly used to support COVID-19 diagnosis.

The findings show that when texture descriptors are paired with other common traits, the algorithms' prediction power rises. Furthermore, integrating various texture descriptor types improves the models' accuracy and yields improved metrics for COVID-19 detection and diagnosis.
The recent pandemic has posed a substantial problem in differentiating between common cold symptoms and those of other respiratory disorders and COVID-19 infections due to the rapid spread of a novel coronavirus strain. Therefore, it has become imperative to create more effective techniques for COVID-19 detection. Among the popular and successful techniques for stopping the transmission of infectious diseases are thoracic X-rays and Polymerase Chain Reaction with Reverse Transcription (RT-PCR). Nonetheless, recent technological developments, especially in the area of machine learning (ML) algorithms, have demonstrated potential to help in medical image diagnosis. Compared to conventional diagnostic techniques, these algorithms provide simpler, faster, and more accurate results.
A recent study has begun utilizing texture descriptors applied to X-rays of COVID-19 patients' lungs in light of these developments. The goal is to identify pertinent features from these pictures and apply them to frameworks created especially for accurately evaluating COVID-19 patients.

This approach involves multiple experiments that employ individual texture descriptors as well as their integration into proposed models. Through these experiments, the study aims to incorporate novel characteristics into the diagnostic process and improve the accuracy of COVID-19 detection.

Moreover, the study intends to compare these newly proposed frameworks against conventional ML models typically utilized in COVID-19 diagnosis. The results of these comparisons highlight the efficacy of incorporating texture descriptors into the diagnostic process. In particular, the prediction effectiveness of the algorithms is greatly enhanced when texture descriptors are paired with other common features. Furthermore, the study discovers that integrating various texture descriptor types increases the models' accuracy and produces better metrics for COVID-19 detection and diagnosis.

Concentrated [11] on identifying picture splicing forgeries, a widely utilized image alteration method [12-13]. The suggested method was tested on six benchmark datasets for effectiveness in retrieving and integrating Markov features from the DWT and LBP domains for splicing identification. The suggested method produced excellent precision results across all datasets using an

SVM classifier that was trained to distinguish between altered and real photos. In [14], a method for detecting forgery in hyperspectral document images was introduced, achieving high accuracies for distinguishing various ink forms. The research provided a comprehensive examination of selecting an appropriate CNN architecture and contrasting classification results with previous methods. A CNN-based method for copy-move forgery detection was presented in [15–17]. It first extracted features from block processing and transformations, then classified the original and altered images. A mask-based tampering technique was used to corroborate the detection process in [18-20], which proposed a feature reduction method for forgery detection using DWT and DCT. Individual picture blocks were compared based on correlation coefficients.

A. ELA

ELA stands for Error Level Analysis, and it is a technique used for detecting image tampering. It works by identifying the differences in compression levels of different regions of an image. When an image is saved multiple times or undergoes manipulation, the compression levels of the manipulated regions tend to differ from those of the original regions, resulting in errors or artifacts that can be detected by ELA [18].

ELA is now a commonly utilized technique, especially in forensic and judicial settings, to identify image forgeries. It can help investigators and analysts identify manipulated images and provide evidence for legal cases. However, it is important to note that ELA is not foolproof and can be fooled by sophisticated forgeries that carefully mimic the compression levels of the original image.

Overall, ELA is a useful tool for detecting image tampering, but it should be used in conjunction with other forensic techniques and expert analysis to ensure accurate and reliable results.

B. CNN (Convolution Neural Network)

The study employs CNN for feature extraction due to its capability to support multiple training epochs and its high precision and recall with numerous input features. In-painting, copy-move forgeries, and picture-wise changes (cropping, histogram equalization, and resizing) are just a few of the image tampering methods that have been developed [21] using CNN. The nature of human vision serves as an inspiration for CNNs, which are composed of non-linear neurons with intricate activation mechanisms. In the context of conflict, watermarking is a commonly used technique for content authentication. Spatial or spectrum domain can be utilized for data authentication. Encryption and steganography can also be used for securing images.

III. METHODOLOGY

This study utilized CNN to analyze and interpret data categories of forged or non-forged images. The process involved five main phases. Firstly, a COVID-19 dataset was obtained and pre-processed. Secondly, histograms were generated for both categories of images. Thirdly, all of the histograms of the photos from both categories were combined into a single CSV file. Fourth, a Python script was created to use CNN to divide the photos into the two main categories. In this phase, the histogram points, weights, and epochs all stayed constant. Final steps included normalizing the histogram data points for each image in both categories and lowering the epoch number from 100 to 50. A 92% accuracy was achieved by updating the CNN weights in accordance with the performance threshold defined in the CNN performance monitor. Figure 2 shows the proposed system's block diagram.

A. Flow Chart

A flowchart is a helpful tool in visualizing and understanding the sequence of steps in a process. In the context of training, a training flowchart can provide an overview of the training process and its progress. Figure 3 presents the training flowchart for the current study, which includes several stages such as dataset acquisition and pre-processing, histogram generation, CSV file creation, CNN training, and performance evaluation. By following this flowchart, trainers and other stakeholders can better understand the different stages involved in the training process and track the progress of the training towards the desired outcome.

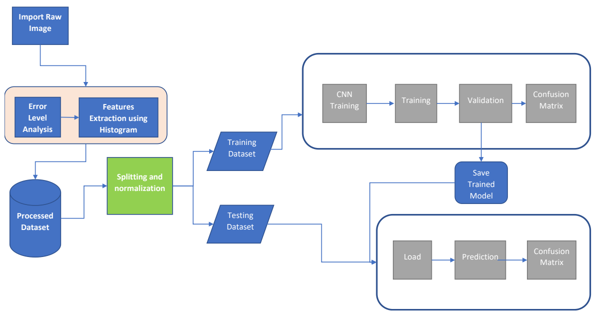

Figure 2: The block diagram depicts the proposed method

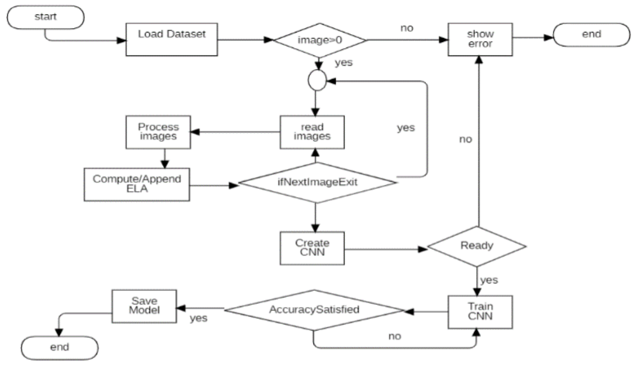

Figure 3: The detailed flowchart diagram for the proposed method

B. Materials And Methods

Even after they have been defined in the abstract, define acronyms and abbreviations whenever they are used for the first time in the text. It is not necessary to define abbreviations like IEEE, SI, Mks, CGS, sc, dc, and rms. If they are not avoidable, do not use abbreviations in the title or headers.

C. Datasets

Github.com, an open-source website, provided the dataset that was utilized to train and test the model [22-23]. Actual chest X-ray pictures of various COVID-19-positive patients were included in the collection. The dataset consisted of 544 photographs in total; 400 (200 original and 200 modified) were used for training, while the remaining 144 were used to assess the model's performance. An illustration of the data used in this investigation is shown in Figure 4.

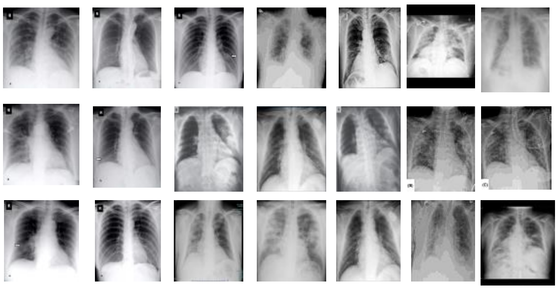

Figure 4: The diagram shows the open sources dataset used in experiments

D. Model Training

The CNN was constructed using TensorFlow as the backend for the Python approach, and the Keras package served as the model provider. The input layer of the CNN architecture included 300 neurons, followed by four hidden levels with fewer neurons (150, 75, 50, and 25), and an output layer with just one neuron. The CNN architecture also had an output layer with six fully-connected dense layers The first five layers employed the Rectified Linear Unit (ReLU) activation function, and the output layer used the Sigmoid activation function. The CNN is a deep learning system that uses neurons with weights and biases that can be learned. Every neuron prioritizes several inputs and uses a weighted total to differentiate between them. After processing the data and applying an activation function (Sigmoid and ReLU), the output is sent to the next layer's input. Fully linked neurons in a layer have complete connections to all activations in layers before it. A graphic illustration of the CNN model is presented in Fig. 5.

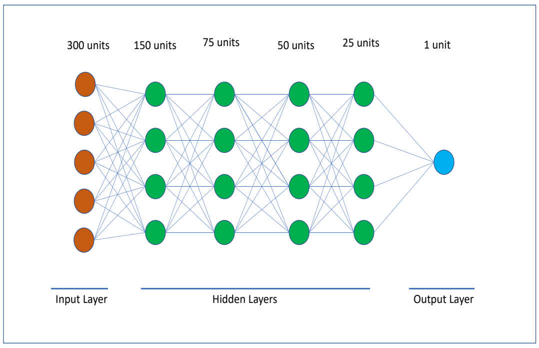

Figure 5: shows the proposed CNN structure

The process of computing ELA of an image is illustrated, and to facilitate better understanding of the ELA concept, Fig. 6 depicts two images, the original image and its corresponding ELA image.

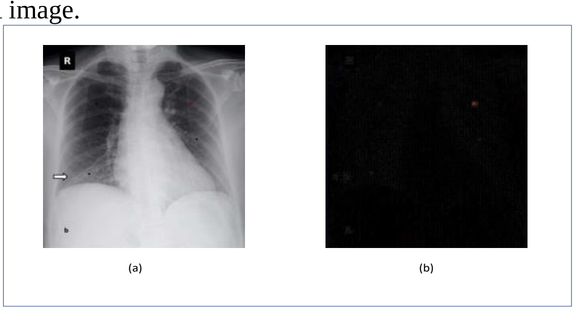

Figure 6: Original and ELA images are show as (a) and (b)

E. ELA Error Level Analysis

Prior to using the machine learning approach, ELA was utilized in this work as a technique for detecting image manipulation. ELA, or Error Level Analysis, is a simple method for detecting changes in the compression of an image, which can indicate the presence of tampering. The working flow of ELA in this study is as follows:

The ELA technique for detecting image tampering involves the following steps: The original image is initially duplicated with a 95% quality of compression. Then, the original and the compressed images are compared, and the difference in pixels is calculated. If the image is unaltered, the change in pixel compression is minimal. However, if the image has been tampered with, the ratio increases significantly.

F. Machine Learning (Neural Networks) for Handling Forgery

The system consisted of two main modules, namely

[1]. The ELA Computer.
[2]. The ELA Forensic.

The ELA Computer module determined the ELA of the input image, which produced a new image of the same size and shape. The updated ELA picture was then sent to the second module, an analyst who examined it to determine whether or not it was fabricated. The algorithm was trained using a collection of seriously manipulated photos such that it could identify forged images when presented with an unknown image.

Through analysis of the ELA picture produced by the ELA computer module, the ELA forensic module in the system is able to identify falsified images. The algorithm was able to correctly identify whether or not unknown photographs were faked because it was trained on a collection of severely manipulated images. The modifications applied to the original image resulted in a notable noise pattern in the ELA of the fabricated image, as illustrated in Figure 8. The original image was modified using the following adjustments to produce a forged version for testing.

G. Confusion Matrix

The original image was subjected to several changes to simulate forgery, including

The application of a sharp orange filter to enhance its view.

[1]. The removal of three visible stars.
[2]. The removal of the green arrow.

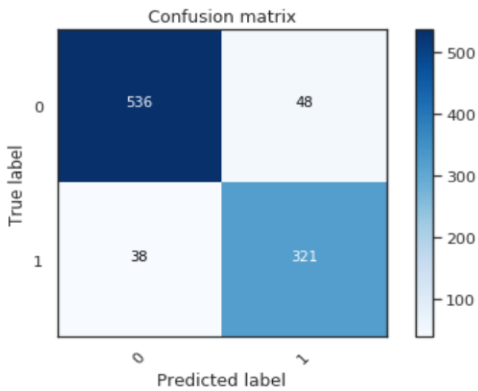

Figure7: Confusion matrix depicts the performance of the proposed method

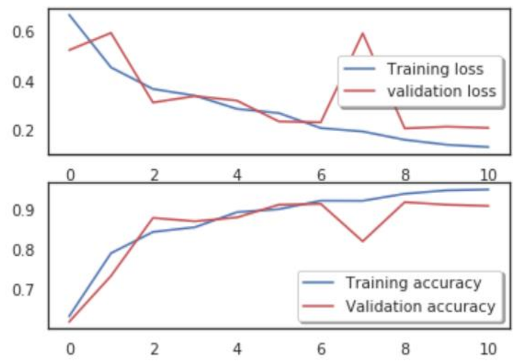

Figure 8: The training and validation accuracy of CNN on the dataset

IV. RESULTS

The accuracy of the CNN was originally about 71%, but it was improved to 92% by making the three changes mentioned earlier, which removed the noise pattern and garbage values from the dataset. In order to further optimise the model, the number of layers was changed, the activation function of the layers was modified, and a more potent optimizer was used. The SGD optimizer was used to get the findings with a learning rate of 0.005. In Fig. 10, which displays the accuracy results over 50 epochs, the blue line represents a constant training accuracy of around 92%, the large red line represents a decreasing validation loss, and the green line represents a low training loss. These findings show that the neural network was trained steadily, accurately, and with little loss.

V. DISCUSSION

Since the COVID-19 outbreak, there has been widespread fear as the number of infected patients continues to rise rapidly worldwide. Healthcare professionals, scientists, and technologists have been working tirelessly to monitor and contain the spread of the virus, develop vaccines, and provide proper treatment. The COVID-19 pandemic has sparked a global study, but despite prior pandemics having an impact on society, there hasn't been much done to predict the long-term economic, sociological, and behavioral effects of the pandemic.

The COVID-19 pandemic has had a disastrous impact on the world. However, in [24], a method for using a hybrid p-CNN and traditional image CNN (image-wised CNN) to perform multi-focus image fusion was proposed, the result turned out to be nearly 25 times quicker than using just p-CNN. The proposed approach was found to be comparable to or even outperform state-of-the-art methods based on both subjective and quantitative evaluation criteria. In [25-26], a new CNN architecture was introduced for hyperspectral image classification. This 3D network used both spectral and spatial data. In [24], a review of various studies related to the automated diagnosis of COVID-19 was conducted. The authors highlighted the drawbacks of conventional research methodologies and showed how these methodologies can be affected by the source dataset as opposed to the necessary medical data. The Generative Adversarial Network (GAN)-based classifier that the authors suggested was trained to avoid learning particular characteristics. Using various source datasets, the GANs-based classifier attained accuracy rates of 97%, 88%, and 66% for severe, moderate, and mild cases, respectively. In another study, the proposed network for hyperspectral image classification was found to be reliable and effective, reducing processing time and improving precision compared to conventional ANN techniques. Additionally, in multi-focus image fusion, a strategy was suggested in [27], which was significantly faster than using a p-CNN directly and was found to be comparable or even better than state-of-the-art methods. Additionally, by utilizing patch-based analysis and majority vote decision-making, [28] developed a neural network architecture that could be trained with a limited dataset. In the meanwhile, [29] devised a specific training approach and explored how to derive a discontinuous binarization function and L2 regularization for weight scaling factors. On the CIFAR-10 dataset, the binary CNN obtained a precision of 92.3% while using the VGG-Small network with these improvements. The method outperformed earlier efforts on the ImageNet dataset, achieving accuracy of 46.1% using AlexNet and 54.2% using Resnet-18. Finally, [30-33] assessed and compared the model performances of four CNN architectures, namely LeNet-5, ResNet-50, VGG-11, and VGG-16. On three datasets, namely ISI, CMATERDB, and NUMTADB, with an image resolution of 32x32, the proposed CNN architecture was applied. The suggested VGG-11 M fared better than the present CNN architecture on hand-written Bangali numeral recognition (HBNR), with highest accuracies of 99.80%, 99.66%, and 99.25%, respectively. A CNN-based segmentation method called U-net was tested in a different study [30] employing a variety of datasets and training data that was taken straight from the visual representation of UAV-based high-resolution RGB photography. This allowed for the fine-grained visualization of vegetation species and communities. With an accuracy of 84%, the method was able to segregate and map different vegetation species and communities.

CONCLUSION

This paper discusses the prevalence of digital data manipulation and forgery, which can be divided into active and passive categories. In the medical field, it is crucial to ensure the authenticity of data to maintain patient trust. The authors propose a model that combines CNN and ELA to extract features from data patches and classify them as either original or forged. The model is trained on a dataset of COVID-19 data and achieves an accuracy of 92%. This can assist healthcare professionals in detecting forgery and ensuring the accuracy of medical data. The authors suggest that future work could involve verifying the performance of CNN using other classifiers.

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