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Exploration of advanced computer technology to address analytical and noise improvement issues in machine learning[☆]

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ABSTRACT

Computer-based visual recognition technology combined with deep learning enables accurate image matching through interactive, multi-level comparison. Currently, popular search methods such as RNN, Faster RNN, etc. are used in computer vision to compute image information by performing hierarchical comparison of image objects. In today's machine learning is used to construct training curves to predict corresponding results, but the accuracy rate will cause some data distortion due to overformation. Therefore, to solve the problem of interference is now physical, the abandonment method is developed to extract certain neurons and reduce the number of feature values. In this study, a visual image recognition framework is designed that uses advanced computer technology to mark and compare images, and to mark and eliminate blurred images. The experimental method successfully improves the prediction of accuracy after a judgment error by comparing the results of training with the results of deep learning verification. The accuracy of matrix formation and result prediction can reach 0.9812 without eliminating the image produced by the light-emitting elements. We remove noisy images based on the same sampling information. After re-training and re-predicting, the accuracy can reach 0.9847.

1. Introduction

Starting from the process of developing software design, it was first developed in data learning technology. It passed the data mining of software systems in the early stage, and carried out the excavation and exploration of the data information originally scattered in different relationships to find out the correlation between them. By marking the feature information, the computer finds out the correlation coefficients of the feature information, further uses the correlation coefficients, develops neural learning models, provides the computer with the simulation of the complex thinking of the human brain, and analyses the relationship between the elements layer by layer, thus achieving the goal of imitating the neural network. In the analysis and training of learning behavior has achieved quite good results. In machine learning, most of the actual analysis data are trained and compared to numerical data known to the computer. Due to fewer sources of interference and the use of image processing techniques for comparison, the accuracy of the analysis is higher. For training, due to problems such as interference, gradient and color shift in image data, when deep learning technology is combined with automatic training, analysis accuracy is greatly reduced. How to effectively reduce and improve the incorrect recognition of the results of image acquisition data caused by interference is a very important issue that needs to be explored. Therefore, the results of sampling training can be automatically checked if the agent service design can be performed by a software system. If image interference information affects the identification of data information, the image is marked, and the error image is imported to remove the analysis results, so as to improve the output result caused by the input image interference.

Therefore, for software automation design, we observe that it is becoming more and more important to find out the relationship between data through software design. We can filter out abnormal image results by using both image learning and

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visual recognition techniques to detect noise in images. It is necessary to create an independent label and let the computer assist us in screening and removing these images with disturbing information. In this study, the automatic comparison technique combined with the mean square error calculation of image recognition technique is used to mark the data with high numerical discrepancy, and gradually reduce the error due to the input error of metadata. The calculation of image visual accuracy is affected by interference noise.

In this paper, the relevant literature and recent developments in deep learning for image-based vision are discussed in Section 2, and the proposed framework and design solutions are discussed in Section 3. Section 4 presents the experimental verification, the import of the image data for the analysis, and the discussion of the results of the experimental verification. Section 5 provides the summary and description of the future research for the sustainable development.

2. Related work

2.1. Machine learning and image vision

Machine learning methods use a dataset to provide complete training data and categories to train a model (Khan and Al-Habsi, 2020; Pei et al., 2017). Based on the accuracy of the training data set, the computer is able to accurately calculate and judge the prediction results during the process of visual annotation. However, in the visual environment, images and data are dynamic and contain various changes, which greatly increases recognition difficulty, especially digital images are disturbed, causing technical difficulties in image recognition distortion.

In order to improve the accuracy of image recognition, it is necessary to use incremental learning techniques (Abhishek, 2020; Luo et al., 2019), such as SVM, to improve the accuracy of image recognition by learning dynamic images efficiently. This method can reduce the error rate by fuzzy computation, but if the input image elements themselves are not clear and clear image patterns, including such digital images in the computation will greatly reduce the accuracy of image vision.

Based on the image training and modeling framework, by first computing and classifying the images, and then filtering out the incorrectly judged category images, the sampling of the auto-detection images that are found to coincide with the noise of the image are excluded and do not enter into the recognition computation. As with the removal of interference factors, this method can adjust the accuracy through data set training and improve the experimental results of image visual recognition (Khan et al., 2021). In addition, it is expected to improve the breakthrough technology in the training model, because we do not need to repeat the algorithm training too many times, and only combine the image of the disturbance with the enhanced learning and the original training method.

2.2. Computer vision

In the field of image recognition analysis research, many of the current studies are focused on the processing of static images and the computation of visual recognition. There are fewer distracting elements in static images. For example, in the most famous number plate information recognition, the number plate is first cut out from the number plate block in the image by the numerical method, and then the image is processed by binarization, black-and-white inversion, and character segmentation. After the processing, the characters in the license plate are finally identified by the optical character recognition technology. In the past, most digital visual recognition was static images, non-dynamic

(x-1,y+1)	(x,y+1)	(x+1,y+1)
(x-1,y)	(x,y)	(x+1,y)
(x-1,y-1)	(x,y-1)	(x+1,y-1)

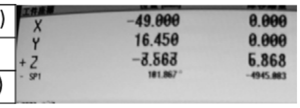

Fig. 1. Example of image transform detection.

flickering images, including image recognition toll system of eTag expressway, the highest speed in Taiwan, with 99.97% image recognition rate (Tao and Fan, 2017). This technology mainly targets the license plate (non-luminous body) for visual recognition and learning training correction. Our investigation will more easily lead to the lack of optical judgment and repeated training, including the technical discriminative dilemma of unclear images caused by the diffusion of light.

However, when a large number of images are trained for image recognition, we still need to repeat the training process through the current training data. In the past, based on the OpenCV environment, many studies have developed the mask R-CNN method to mark the images that are expected to be updated for training (Ugwu et al., 2022), by In the same training data, it can be gradually found that the accuracy of its images has increased from 95% to 97% by research. From this, it can be seen that although there has been a reduction in the amount of noise information, the accuracy of computer vision can be improved by repetitive training.

Through the basic image processing technique, including the average filter operation to reduce the noise in the image, and bright light. The background is set to negative, the dark foreground is set to positive, the third step is to set the threshold to enhance the foreground, then perform noise reduction processing, remove the remaining noise, and mark the target block, and finally use the neural network to identify numbers to generate results. As for the OKM-CNN method (Pustokhina et al., 2020), through the experimental results, we can find that if its accuracy is flat and non-illuminating interference, only static interference such as shadows and stains, the definition of image sampling still has certain remarkable results.

2.3. Image sampling

During image sampling (Gupta et al., 2007; Peng and Wang, 2020), image difference data will be computed. In the process of image learning and training by OCR, we need to divide the photo into neatly arranged particles, and then assign each particle a value representing the brightness of the particle. The same spatial division and the same numerical representation of the brightness are collectively referred to as digitization or discretization. Indicators of image clarity can be distinguished by the differently marked image features on each image; digitized photographs are referred to as images, and black and white or grayscale images are simply images. It is the 2-dimensional brightness function f(x,y), in which x,y are the spatial coordinates of the 2-dimensional image and the function value f is the brightness or intensity of the (x,y) point.

We assign different position images to the marking method, perform an image check comparison for different markings, and mark the images with high interference value to show that when we resample the image. This standard method is designed to facilitate the comparison of similarity and noise, since the image sampled in this experiment is a 3 × 3 matrix. In the future, the marker comparison of the automatic detection frame size can be included in the image sampling frame larger than 3 × 3 (see Fig. 1).

2.4. Image data analysis

In data image analytics, the information in the image coordinates can be viewed and further compared with related data. Our research found that Hough transform (Duda and Hart, 1972) is a well-known algorithm for detecting specific geometric structures in images. The digital image of the plane is adjusted to the corresponding value of the image coordinates by the Hough transform, and then the space is numerically transformed to transform the image from the coordinate space to the parameter space. The most likely to detect the position of the geometric figure.

Another researcher, Docstrum (O'Gorman, 1993), proposed to locate the image coordinate axis first. It centers the document in a bottom-up manner and in the center of the document in a relevant manner, based on the image-centric slice structure. Within the range of the device, it fragments several nearest neighbor text links, statistical clustering links, size and distance parameter areas, and so on from small to large.

In our research, we are trying to improve the accuracy of search analysis and the reduction of image noise interference. With the help of the above method, the analysis target is located and cut, the noise of the interference source is reduced, and the target result is accurately analyzed.

2.5. Edge and cloud computing

Edge computing can support applications such as resource management, equipment management, and instrument control by using digital cameras for image capture and analysis. In recent years, edge computing has mostly been used to solve last-mile data modeling problems (Deng et al., 2021; Wu et al., 2020). Image recognition accuracy can be greatly improved by using this technology for learning and classification, and by screening noisy data before machine learning. As a precaution, companies are now using deep learning or artificial neural networks called convolutional neural networks (CNNs) to mimic human vision. Using CNN to stimulate learning requires high-speed computers for image processing.

Another advantage of edge computing is the ability to pre-screen and reanalyzed the front-end of a distributed system, such as a network, before it is connected to the network. For example: If two pupils are looking at the mathematical formula on the board at different places in the classroom, one of them might see an error in the way the teacher has written it, while the other might not. Therefore, the results of the early warning after the edge computing can eventually improve the performance of the computer vision computing by centralizing the computing and sending the relevant data to the cloud. Reduce environmental protection construction costs through return on investment. A custom image processing module for edge computing will check the image data for each model, and only those images that are reasonably trustworthy will be sent to the cloud for further processing. The amount of data sent to the cloud is reduced by sending only selected images, reducing costs.

2.6. Optical character recognition

The OCR recognition technology is quite mature now. Many studies use this technology to convert files, including files, extract text, etc. The core technology of OCR involves the following two steps. Preprocessing the image to be recognized. Marking the text field to minimize interference with the character recognition. Common methods of pre-processing images include zooming, binarizing and denoising (Zhang, 2010). The pre-processed image is then recognized, and the result is the text content of the image recognition (Vaishnav and Mandot, 2020; Wei et al., 2018). In recent years, due to the maturity of deep learning technology, many studies have started to analyze photo images (Kim et al., 2023; Gautam et al., 2023). Many deep learning OCR technologies have been released, and the use of deep learning has improved the accuracy of image recognition. There are two types of deep learning OCR methods. One of them is divided into two stages of text detection and text recognition (Karthikeyan et al., 2021). The other is the text detection and text recognition of the whole model at the same time. This research will use OCR technology to digitally sample and analyze the luminous image. Get the position of detection coordinates by marking the image and converting and calculating the digital result of the image with deep learning.

In the case of text-based image recognition, the text recognition that can be used is the detection of the area in which the text is located in the image. Distinguishing between the text and the background is most important. CTPN and EAST are common algorithms for text detection. Text recognition is the process of identifying the text in the box after the text box has been located in the image. Commonly used methods include, but are not limited to, the following CNN + Softmax, CNN + RNN + Attention.

Tesseract is a suite of exclusive programs that was developed by Hewlett-Packard Labs in 1985. In 2005, the transformation, debugging, optimization, and open source of Tesseract was taken over by Google (Songa et al., 2022). The current Tesseract code is also hosted on the github project. Therefore, the use of Tesseract in search is not for the recycling of the text template, but for accurate OCR recognition after Tesseract's detection of image perturbation events.

3. Data set and design solutions

In the research architecture, due to the need for pre-image learning and classification in edge computing environment, the research uses MQTT communication mechanism, and the edge devices' data processing results are communicated with the core server via network communication. When the node receives the image, it can first perform the classification of the digital image. Assuming that there is no interference flickering state in the image classification, it can be confirmed by sampling through a Creative Image Detection Module (CIDM) designed by us, and the obtained image can be classified by visual comparison to find out the residual information of light and shadow in the image.

Since our edge computing system will compare the sampled data with the previous sampled data through skimage.measure. compare_ssim. A comparison of the differences between the before and after images is made when an edge device captures an image. If the difference between the before and after images is too small, it means that the image similarity is high, then a flag is set to filter the image and the data image is not evaluated.

The Structural Similarity Index Metric (SSIM) (Peng et al., 2020; Cao et al., 2023) is used in the verification method. SSIM is a metric that can be used as a measure of the similarity between two digital images (Sara et al., 2019; Scazzoli et al., 2019). To reveal structural information about objects in the scene, we use SSIM correlations between neighboring pixels in natural images. It is more suitable for image quality assessment and scene change detection, such as the human eye in the monitoring process where x and y are the two test images; x and y are their variances; x y is the covariance. c1 and c2 are constants. The value range of the SSIM is from 0 to 1. The larger the value of the SSIM, the greater the similarity between the two images. When two images are identical, the value of SSIM is 1. The limitation of SSIM is that it cannot effectively handle non-structural distortions such as image shift, scaling, and rotation. However, in our experimental

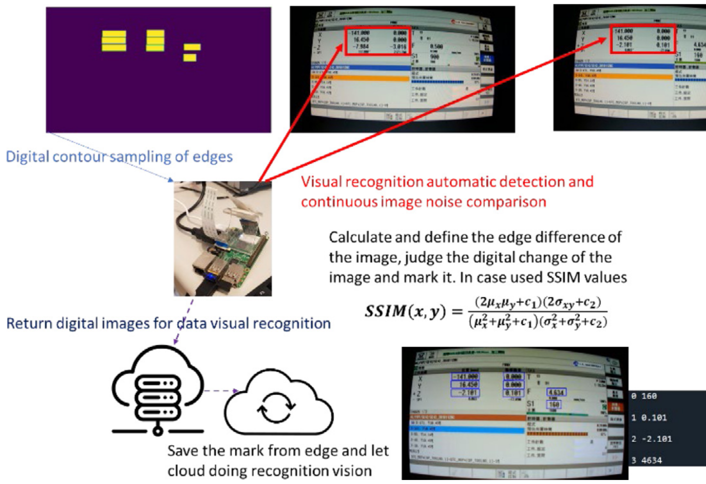

Fig. 2. Overview of the overall experimental design.

environment, we have a stable environment in which the camera is fixed in front of the display screen.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (1)$$

For the numerical calculation, before and after the image comparison, we retrieved the image and performed the numerical analysis of the difference image detection. For the SSIM value falling between 0.85 and 1, we observed that most of the images in this interval contain halo scattering and the image is not clear. Due to the misjudgement of the value extraction and calculation, we first exclude the images in this section from the learning calculation model in the experiment to further improve the misjudgement of the extraction and identification value generated after image sampling.

We use the image of the node for computation and identification after edge computing sampling. Assume that the system model raises three task events when the image changes. First, to verify the feature points, the image data is compared with the previous image. If the verification result differs from the previous image, the image number and edge computing device number are returned to the cloud database. In computing network communication through edge nodes, we use MQTT to return images to the core image analyzing and recognizing platform through a low-loss communication mechanism. Finally, after the images have been obtained by the core image analysis and recognition platform, the images are sampled for data recognition. Meanwhile, the collected images will be viewed, the digital interference images will be removed, and the recognition results will be written into the database. Simultaneously, through another communication channel, the images with high noise are sent to the cloud platform to build a library of interference noise. MQTT transfers the database data when sending to the terminal device, the same number with the same interference factor will not be calculated and sent in the future image vision. This reduces the computing cost of the edge device and improves the network transmission efficiency. Fig. 2. Diagram of the complete experimental model

In the process of edge computing, if the difference of the visual analysis results is small, the sampling state of the system is the same visual image, and no subsequent image analysis operation is performed. For this reason, the use of image pre-processing software at the frontend can help reduce and filter out unnecessary image information. A terminal visual recognition model is constructed, and the model system is placed in the Raspberry Pi environment for front-end image visual recognition.

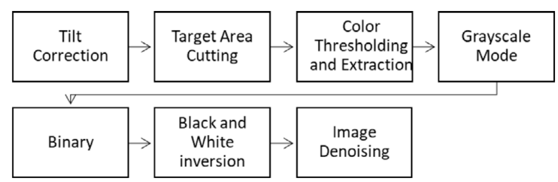

Fig. 3. The Image processing flow.

The structural index similarity measure and mean square error for simultaneous detection are used in this study. When the training model is calculated, when the numerical influence values are different, the experimental results are shown in the following figure. It can be seen from Fig. 7 that the variation range of the MSE segment is relatively numerical, and it is difficult to effectively limit the evaluation of the differences in the image recognition. We observed that clear values of SSIM were sufficient for classification analysis when SSIM values were between positive and negative values of 0.1 samples as the reference marker base. After edge computing, when a change in the image is detected, the image is sampled and analyzed and sent to the cloud server. The image information is numerically sampled and learned by the cloud platform, and at the same time, a flag is created. If the flag information is 0, it means that the flag is invalid, and if analysis is required, the system will use the previous raw analysis results. If the flag information is 1, it means that the image of the flag has been changed, and the data image will be returned for the analysis of the image visualization.

Once the frames are sampled, we first calculate the difference between the frames. We first perform noise pre-processing on the image to calculate the noise level of the image, and decide whether to continue the calculation and analysis by image recognition, because two consecutive digital images may have error values during image calculation. The image must be processed first to make digital recognition more accurate. The processing method and process are shown in Fig. 3, which are slant correction, target area cutting, color threshold setting and extraction, greyscale mode, binarization, black and white inversion For transfer and image denoising, through seven operating processes, data can be extracted from image modeling, and can be monitored and tracked by writing back to the database, and image model correction can be performed on machine learning results to complete the goal of improving the performance of analysis results.

In light source image recognition technology, due to the light interference problem of LED matrix numbers, the numbers

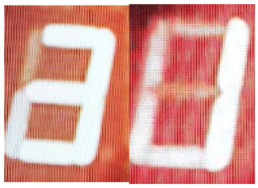

Fig. 4. Unrecognizable interference data sample.

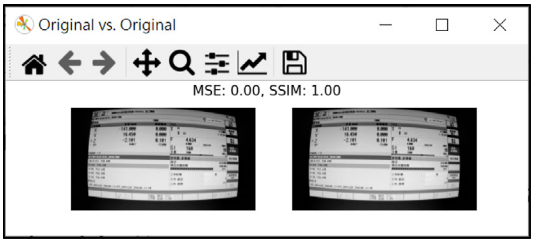

Fig. 5. The image is verified against the same control data.

recorded by our camera are different from traditional paper images. For images with bright light, the sample data may have lost its analysis value due to the sample interference during the capture. The probability of system distortion will only increase when this data is used for deep learning analysis. The distortion rate increases with the number of images that are captured, and the distortion rate increases in relative terms. As can be seen in Fig. 4, this is because the machine is shooting continuously and automatically. The sampling of images can still not be really guessed by human knowledge, and the digital information cannot be understood and acquired.

4. Experiment description

4.1. Contour computation for image deviation detection

For the images that we want to retrieve from the edges, we first sample the reference values of the image. Through the sampling of the end device, we do the SSIM value detection on the image. As shown in Fig. 5, after sampling the same image, the original baseline, MSE=0.0, SSIM=1.0 is obtained.

Due to dynamic calibration, in the experiment, the images are taken sequentially on the time axis. It is assumed that four images are taken sequentially. In the state of time series, we compare and calculate the images captured by different machines, and check and inspect the flickering or obscure parts of the image. The list of images used for comparison is shown in Fig. 6.

We keep taking pictures and get different pictures. So we can verify the following pictures. The original image is the first image we captured in the webcam image when comparing two images chronologically. In this case, we will try to find the SSIM values by using the Contrast 1 and the Contrast 2.

In the comparison of the original image with Contrast 1, MSE = 155.95, SSIM result = 0.90. The system automatically adjusts the differences between two images in the Image Library. When the SSIM changes, it is possible to check if the image flashes when it is unrecognizable. The visual result of the focus display is shown in Fig. 7.

For information about the image, we continue to move the time axis backward. Comparison of Contrast 1 and Contrast 2 in the time image, MSE=213.6, SSIM=0.88, according to the search for MSE Contrast 2 and Contrast3. Different values can be obtained from these. From the result, we can get the value that proves that the variation involved in the different images leads to a still localizing image. We compare the interfering images and reject the images compared to this value based on the value of the localization image. Therefore, the assumption is that within the SSIM interval = 0.88 and SSIM = 0.86. If the same image data or similar data is obtained by the visual inspection, our model can obtain the quantitative limit and set the standard for the analysis.

4.2. Training and analysis of the image information

Traditionally, machine learning has been used in a variety of fields. At present, it has been developed for the calculation of data through algorithms to predict the accuracy of the next transaction or information. Due to the development of artificial intelligence problems, many studies start from deep learning. Deep learning learns the characteristics of the data itself in a multilevel nonlinear way, and gradually connects two unrelated events. Therefore, we begin with sampling examples of images that we want to train. After sampling, we mark the position of the number. The combination of the recognition method and the digital content training method, and the recording of the numerical data one by one. When we remove it for verification, the result of the driving motor calculation has missing values and is inconsistent with the previous and previous values. It is manually selected for verification. Finally, the selected samples are recycled. Based on the training results, it can be seen that the accuracy of discriminating is improved when the device is selected first (see Fig. 8).

In the experiment, we took 60,000 images sequentially. First, we conducted automatic image learning training, and then tested another 10,000 images. The automatic detection accuracy after training can reach 98.12% by checking the value of image analysis, comparing and extracting the numerical information, and comparing the numerical result of the image obtained by machine learning with the numerical result of the photo tag.

We will eliminate the images with the SSIM values higher than 0.8, and target the images with the high rendering similarity that are generated by the optical reduction optics and the photos that are the same as the previous image. Once removed, the pictures are trained, analyzed, and compared with the correct outcomes of the original labeling. After the training, the accuracy of the automatic detection has been increased by 3%, and the experimental results have verified that after the removal of interference images, it is helpful to improve the accuracy of the optical image digital comparison analysis.

Based on the results of our experimental study, we have observed this in our calculations of optical image discrimination. The accuracy of matrix formation and result prediction can reach 0.9812 without eliminating the image produced by the light-emitting elements. We remove noisy images based on the same sampling information. After re-training and re-predicting, the accuracy can reach 0.9847. The method of this study has been verified by means of experiments. It can remove noisy images, and then perform image recognition training tests. This can improve image recognition (see Figs. 9 and 10).

5. Conclusion

The use of edge computing in combination with image verification models can improve the accuracy of machine learning for image verification. After the investigation and verification of the image, the image is compared with the image before the deep learning to eliminate the wrong image of the interference. This study proposes to improve the traditional continuous collection of data image samples and eliminate wrong images for analysis and computation, by combining edge and cloud experience analysis. Experimentally proven edge computing is used for screening

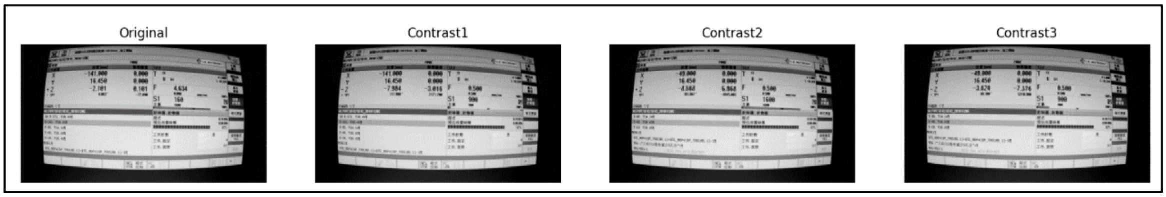

Fig. 6. Compare the image to another contrast.

Fig. 7. Time-series comparison of video data.

Fig. 8. Example of Camera Sampling.

Fig. 9. During training, the original model did not remove distracting images.

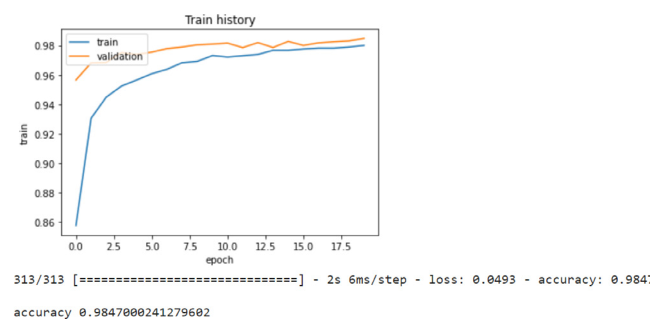

Fig. 10. During training, the original model removes distracting images.

and validation. Through machine learning, the traditional digital image recognition is applied to image vision in front-end technology applications. After the acquisition of the data images, we further analyzed the results. From the experiment, it can be seen: The recognition accuracy is improved by 3%.

Due to interfering images or unclear images, the previous data analysis results may be accurate, but due to the interfering images added during training, it will cause misjudging after calculation. In this study, the proposed innovative architecture is used to eliminate the interfering images by image computation, reduce the interfering information, and allow the machine to compute the real results more accurately during training and learning. It can be found in the experiment that this method can not only Improve the accuracy of image recognition, and reduce the cost of computing, because the total number of image analyzing is reduced.

By redesigning the image calculation rules and the two-stage verification model, the digital images are checked in hierarchical order, and the images are uniquely verified. This method of calculating and processing similar and identical images reduces image interference signals and sends only images that can accurately calculate results to the cloud platform for calculation. This search method can reduce the likelihood of incorrect judgments when recording data images after image recognition. Subsequently, it can be used on the LED home screen, which can obtain data and judge results more accurately by improving the accuracy of image recognition. Therefore, the initial screening of edge devices can actually improve the image analysis and identify the differences after learning the physical model. The effectiveness of our method is confirmed by the experimental results, effectively improve and reduce the likelihood of bad decisions. A model for the architecture of the verification and identification process is provided in this study. In future research, we can apply the technology to more recognition applications that need deep learning, through appropriate training, the ability to visually recognize images under disturbing and noisy conditions can be improved.

CRediT authorship contribution statement

Tse-Chuan Hsu: Conceptualization, Methodology, Software, Writing – original draft, Supervision. **Yao-Hong Tsai:** Methodology, Validation, Formal analysis. **William Cheng-Chung Chu:** Visualization, Investigation, Writing – review & editing. **Shyh-wei Chen:** Visualization, Investigation, Writing – review & editing. **Hung-Lung Tsai:** Methodology, Data curation, Funding acquisition. **Yu-Kang Chang:** Visualization, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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