1 **INTRODUCTION**

2 **ARCHITECTURE OF CNN**

3 **APPLICATION OF CNN**

INTRODUCTION

Convolutional Neural Networks (CNN) are artificial neural networks that are commonly used for image analysis. CNN may also be implemented to overcome various data analysis and classification concerns. In general, CNN has some form of expertise for detecting trends and anomalies sense of them. CNN's ability to discover patterns is what makes it so beneficial for image analysis. CNN contains hidden layers known as convolutional layers. These layers receive input, change it in some method, then send the output to the next layer, which is called a convolution operation. These convolutional layers are the ingredients of recognizing the patterns in CNN. It specifies the number of filters the layer should have to identify any pattern. Filter is an integer matrix that is used to recognise complicated objects. These filters grow more sophisticated as the network depth increases. For example, in the beginning of a network, the filter may identify simple geometric filters like edges, corners, circles, and squares, but later layers may be able to recognise particular items such as eyes, mouth, hair, feathers, or even larger objects like dog, face, and many more.

CNN are commonly used for image classification, such as categorizing handwritten characters and numerals, face detection and detecting highways in satellite photos. There are other more common jobs that CNN can implement including picture segmentation and signal processing. Picture segmentation is a method of breaking up a digital image into smaller groups of pixels called picture segments. This process is to reduce the complexity of the image and make further processing or analysis of the image easier. For example, the picture segmentation is implemented in designing the vision for autonomous vehicles, such as self-driving cars. The method helps to assist the system to locate and identify other objects on the road. Signal processing is a method to analyze, modify and synthesize the signal which is able to enhance signal transmission, increase bandwidth utilization, and improve perception quality, as well as highlight the significant components in a measured signal. The signal received can be in terms of picture, sound, or any scientific measurements. Signal processing has been implemented in the biomedical field, for example, application in Distortion Product Otoacoustic Emissions (DPOAE) testing. It is an auditory testing which is used to detect the functionality of a cochlear amplifier in the ear canal, when the DPOAE is missing, it means that the amplifier is not functioning properly and that there is hearing loss.

ARCHITECTURE OF CNN

Convolutional Neural Networks (CNN) is a type of neural network that focuses on processing input with a grid-like form. It is formed by a stack of discrete layers that use a differentiable function to turn an input volume into an output volume. It is generally composed of three layers, convolutional layer, pooling layer, and fully connected layer.

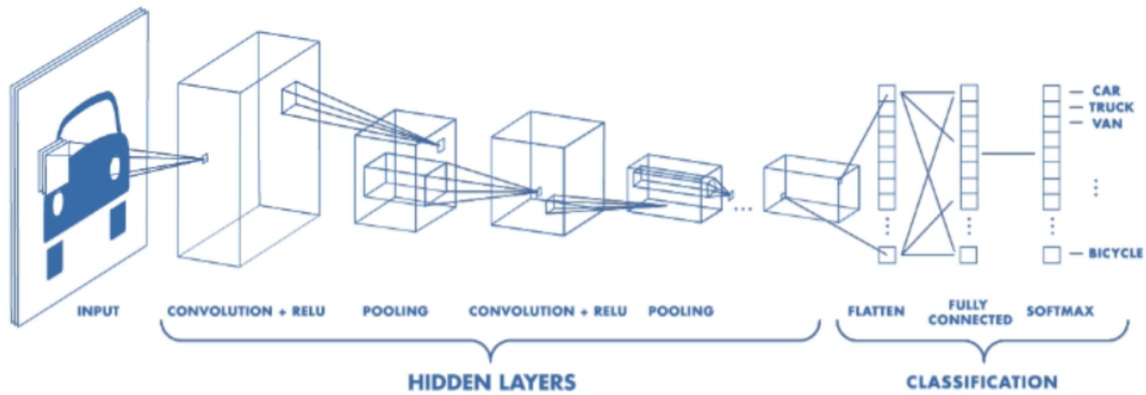

Figure 1: Illustration of Convolutional Neural Networks Architecture

The first layer is called convolution layer, this layer is the core process in CNN. This layer is where a learnable filter (kernel) is chosen to convolve over the input value which rolls over its width and height and performs a dot product between the filter and the confined area of the input patch to produce a 2-dimensional activation map of that filter. This is what is called a convolution operation. Next, pooling layers or downsampling/ subsampling. This layer replaces the output, it helps reduce the output representation's spatial size. The most popular pooling function is max pooling, this process reports the maximum value from each feature map patch. The results of this operation are pooled feature maps that emphasize the most significant feature in the patch. Lastly, a fully connected layer, this is the feed-forward neural networks that locate at the last few layers in a network. The final output from the convolutional layer or pooling layer is the input for this layer, which is flattened before being transferred into the fully connected layer. Neurons in this layer have complete connection with all neurons in the network and following layers. As a result, it may be calculated using a matrix multiplication followed by a bias effect. This layer helps in mapping the representation between input and output.

APPLICATION OF CNN TO STEM CELL BIOLOGY

Convolutional Neural Network (CNN) is now being utilised for a variety of purposes, including medical issues. Kusumoto and Yuro (2019) believed that convolutional neural network would have a significant influence on stem cell biology research. Induced pluripotent stem cells (iPSC) has become a well-known medical breakthroughs in recent time, which have a variety of applications in regenerative medicine, personalized medicine and disease modelling. iPSCs are used when they have differentiated into particular cells that can be identified using molecular approaches like immunostaining and lineage tracing. For each cell in iPSCs, it has a distinct morphology, therefore, a CNN morphology-based cell type recognition system would be a feasible option.

Using deep learning technology, Kusumoto and Yuro built an automatic recognition method for iPSC-ECs that does not need molecular labelling with accuracy > 0.9 and F1 score > 0.75 to detect iPSC-ECs with great performance. High-quality datasets in a huge number was prepared before developing an image categorization system. Although the implementation of an algorithm allows less datasets to be used, accurate learning requires over 10,000 images.

Figure 1 shows the approach used for identifying iPSC-ECs. Based on random phase contrast pictures, CNN was used to estimate whether target blocks from the input dataset were endothelial cells or non-endothelial cells. The difference between the findings of CD31-immunostaining and CNN prediction were analyzed, then the CNN's weights were optimized using the back-propagation approach. Although hyperparameters influence learning efficiency, dataset production, including input data quantity, answer threshold (endothelial cells/non-endothelial cells), and network kinds, is critical for improving prediction accuracy. The accuracy of prediction of CNN is also affected by its complexity and. Deep learning-based morphology-based identification algorithms offer a substantial benefit in the actual application of iPSCs since they are intuitive and adaptable.

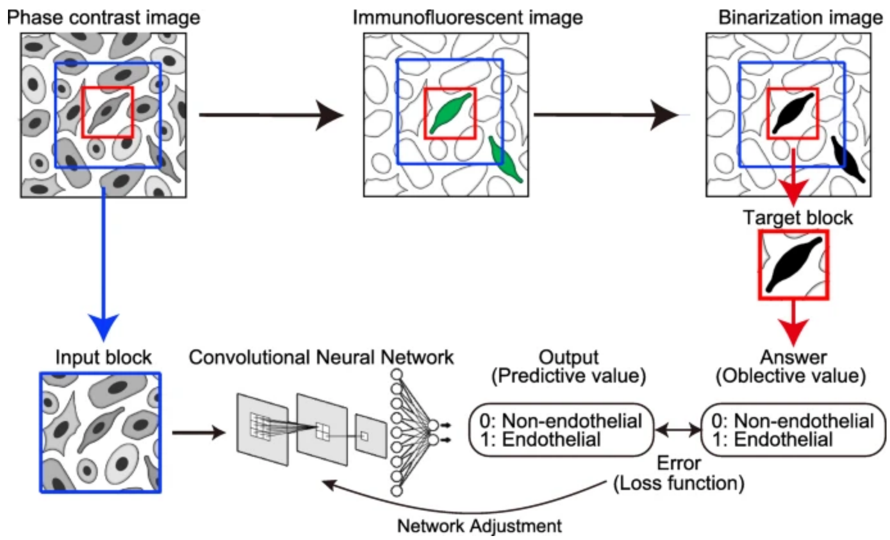

Figure 1: Approach used to identify iPSC-ECs by CNN

3.2 APPLICATION OF CNN IN CLASSIFICATION OF HIGH RESOLUTION AGRICULTURAL REMOTE SENSING IMAGES

Precision Agriculture (PA) has been growing rapidly over the years. Because of that, crop classification using high-resolution remote sensing images become feasible in the process of estimating and managing in agriculture. Chunjing et al. (2017) developed a convolution neural network-based classification algorithm for high-resolution agricultural remote sensing photos.

Chunjing et al. used an abundance of training samples obtained by panchromatic images of China's high definition satellite, to visually categorise the crop photos of Ezhou, Hubei. The significant temporal and spatial features of the crop is focused to provide the overview of crop production in Ezhou. Rice is the principal grain crop in Ezhou, whereas rape is the main cash crop. Lotus root, cotton and others are also planted. Figure 2 shows the crop photos, each labelled with their own category.

Pond	Rice	Algae	Waste-land	River	Build-ing	Wood	Road	Plant-ing
0	1	2	3	4	5	6	7	8

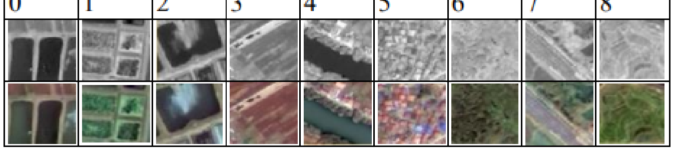

Figure 2: Category-Label-Image

Based on the figure above, 1,500 data sets were generated by repetitive manual identification, and after the rotation, 6,000 of the data sets were obtained. 80% of these data sets were used for convolutional neural network training and 20% being utilised for verification. After progressive optimization of altering parameters, the final parameters are specified; The convolution core is 7*7, batchsize is 50, learning rate is 1, activation function is sigmoid and training time is 1. Finally, the result of correctly classified crop is 99.66% accuracy. The convolution neural network model has a significant impact on decreasing errors because of zooming, picture translation, tilting, and others.

The comparison studies with alternative classification methods is conducted in order to validate the efficiency of CNN. The findings of CNN are better than those of existing approaches. Therefore, convolution neural network application clearly improves the accuracy of image recognition and classification for the field of remote sensing in precision agriculture(PA).

Method	Supervised (panchromatic images)	Supervised (multi-band images)	Unsupervised	SVM	CNN
Overall Accuracy	14.7%	87.66%	44.6%	80.7%	88.87%

Table 1: Different Classification Results

APPLICATION OF CNN IN LICENCE PLATE DETECTION

Convolution neural networks (CNNs) have significantly improved performance in numerous tasks, including face identification and recognition and offer a fresh approach to the challenge of identifying licence plates. This task is still difficult, though. Since it is challenging to detect small licence plates, state-of-the-art systems using CNNs at the licence plate detection stage are unable to resolve the issue with varying scales of licence plates when the camera is fixed at different angles and heights. The four areas of edge information, texture information, colour information, and machine learning provide the foundation for licence plate detection techniques. The technique based on edge information obtains the candidate region of the licence plate by employing the edge feature of a licence plate to segment connected areas, and the fake licence plate is then eliminated using the gradient of the candidate region and entropy. Such techniques struggle in uncontrolled contexts because they rely so largely on the image's edge information.

To test a data set for character recognition, an experiment was run. 40,000 licence plates generated roughly using the approach for automatically generating training data because the CNN model needs more than 2000 training data from real scenarios tagged artificially. 2000 training data added from the real situations to the training data set to make it more complicated and prevent over-fitting. With the same training data for contrast, a conventional approach (HOG + SVM) is also taught. Character recognition performance comparison is shown in table below.

Methods	**Accuracy**	
	data all from generation (40000)	add data from real scenes (40,000 + 2000)
CNN	0.92415	0.96782
HOG + SVM	0.87973	0.89355

Table 2: Character recognition performance comparison.

APPLICATION OF CNN FOR COUNTING PEOPLE

One of the most crucial functions of intelligent video surveillance systems is people counting, which has a wide range of uses and business value in various locations, including banks, train stations, retail centres, schools, etc. Due to low resolution, occlusion, changing lighting, imaging perspective variations, and backdrop clutter, counting persons in a crowded surveillance area is a difficult task. The fundamental idea of the techniques is to create a detector that can identify every person in order to count the number of persons. The most often used detection techniques include head detection, shoulders detection and body detection.

As illustrated in figure below, 4000 frames of pedestrian passage video walking with a lot of mobile personnel were taken from a crowd video database first introduced in. A training set of 1200 frames for learning the regression function and a test set of 2800 frames make up the database.

The methods of Subburaman and Goldberg are chosen to be used on the crowd video database in order to compare the crowd counting findings. At 100 frame intervals, 20 frames are taken out of the video. Table below shows that the proposed algorithm's MAE and MRE are both reduced. In other words, the suggested system predicts crowd size more accurately. It can be seen that the proposed method's estimated crowd counts comes the closest to being accurate. As a result, compared to previous methods, the statistical findings of the suggested method show higher recognition accuracy.

Method	MAE (%)	MRE(%)
Subburaman	23.16	45.96
Goldberg	38.98	88.92
Proposed	17.49	38.32

APPLICATION OF CNN FOR FRUIT CLASSIFICATION

Fruits play a crucial role in our daily lives as a food. It delivers nutrients that are essential for our health and bodily upkeep. More fruit consumption as part of a healthy diet is likely to lower the risk of developing various chronic diseases. But not all fruits are treated similarly, and it is troubling that not everyone is knowledgeable about each fruit. Fruit classification is a good method that can help people to know more about fruits. This approach can guide us in choosing fruit that is right for us and instruct us on the traits of that specific fruit. These kinds of programmes can aid in educating kids and introducing them to fruits.

The tasks of object recognition, segmentation, classification, and image processing can all be prepared for a CNN. Large public picture databases like ImageNet have made large-scale image recognition possible. Similar to the neurons in the human brain, CNN are networks. A CNN is illustrated in the figure below. These neurons are made up of weights and biases that arrange themselves into layers and fire in a specific order to produce an output. By providing the networks with a lot of data, they may be trained to recognise specific patterns. This means that a computer may be taught to recognise various objects, which is highly helpful in the field of computer vision.