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# SCALE-BASED CLASSIFICATION OF AERIAL PHOTOS

**Dr. Indu Bhushan Lal**
Senior Assistant Professor, Department of Information Technology, L. N. Mishra College of. Business Management, Muzaffarpur Bihar

**Dr Manish Kumar**
Principal, Vidya Vihar Institute of Technology, Maranga, Purnea

**Arunabh Kumar**
Research Scholar, Department of Electronics and Communication Engineering, Eklavya University, Damoh, M.P

**Abstract-**In the future, it might be challenging to find a solution to the challenge of categorising aerial pictures only on the basis of their spectral content. A convolutional neural network, also known as a CNN, was constructed in order to classify aerial photographs into seven distinct types of ground cover. These categories are as follows: building, meadow, thick vegetation, waterbody, pointless arrival, street, and shadow. The classifier made use of the spatial as well as the spectral information contained within the data in order to improve the accuracy of the categorization handle. The initial preparation that CNN undertook consisted of the creation of ground truth tests in tangible form. The design of the arrangement consisted of a single convolution layer with 32 channels, a bit estimate of 3 3, a pooling estimate of 2 2, clump normalisation, dropout, and a thick layer with Softmax enactment. The engineering design and its hyperparameters were chosen based on the results of testing on the system's affectability and approval precision. Based on the findings, it appeared as though the proposed model would be an effective means of classifying the ethereal photos. The total precision and Kappa coefficient of the demonstration that was the most accurate were, respectively, 0.973 and 0.967. Also, the affectability study recommended that CNN implement the dropout and bunch normalisation technique in order to move the generalisation execution of the programme forward. The CNN demonstration would have had a less satisfying end if those procedures weren't taken; the overall precision and Kappa would have been 0.932 and 0.922, respectively, instead of the higher values. According to the findings of this research, CNN-based algorithms perform admirably when used to the task of arriving cover categorization utilising ethereal images. In any event, it is essential to correctly select and optimally configure the design and hyperparameters of these models.
Key words: CNN, Clump Normalization, Scale-Based Classification, Aerial Images.

## INTRODUCTION

The classification of additional detecting information, particularly orthophotos of three bands of red, green, and blue (RGB), can be challenging when using traditional methods [1, 2], despite the fact that several literary strategies have demonstrated great outcomes. The fact that the total amount of labelled information is significantly less than the overall estimate of the dataset is the most significant factor that contributes, and the fact that inaccessible detecting datasets have high intra- and interclass changeability [3] is another factor that contributes. However, more recent breakthroughs in deep learning approaches, such as convolutional neural nets (CNNs), have exhibited promising results in the categorization of images that are particularly challenging to detect [4–6]. In particular, hyperspectral images have shown the most promise. The benefits of deep learning algorithms include learning high-order highlights from the information, which are frequently more valuable than the raw pixels, which are used when classifying an image into a few given labels. In addition to this, these strategies involve the spatial learning of pertinent facts from information by means of highlight pooling from a limited spatial region [3]. A large number of analysts have used a limited number of methods and computations with great effectiveness, enabling them to accurately deliver arrive cover maps and classify a very high-resolution airborne image. Methods such as object-based picture analysis, also known as OBIA, have been examined rather frequently because of the benefits they offer in terms of the creation of extremely high-resolution photographs that make use of strange and spatial highlights. In a recent article, Hsieh et al. [7] integrated aerial photo categorization by combining OBIA with a decision tree using surface, form, and alien inclusion. This was done in order to connect the two methods. Their research yielded results that were accurate 78.20 percent of the time and had a Kappa coefficient of 0.7597. Vogels et al. [8] combined OBIA and arbitrary forest categorization using surface, slant, form, neighbour, and spectral data to construct classification maps for agricultural zones. These maps were produced so that agricultural zones could be properly mapped. They tested their calculations on two different datasets, and the findings demonstrated that the methodology that was utilised performed effectively, achieving accuracy rates of 90% and 96%, respectively, for the two different research zones. 12 pages are included in the article with the identifier 7195432 from the Hindawi Journal of Sensors. Nonetheless, Meng et al. [9] proposed a novel model in which they combined OBIA to advance vegetation categorization based on ethereal images and global situating frameworks. This model was presented in the context of advancing vegetation categorization. The findings demonstrated a substantial increase in classification accuracy, which increased from 83.98 percent to 96.12 percent overall and increased from 0.7806 to 0.947 in the Kappa esteem. In addition, Juel et al. [10] shown that the application of a computerised elevation model can help arbitrary forests reach a reasonably high level of performance for vegeta- tion mapping. In a more recent article, Wu et al. [2] presented a demonstration for identifying ethereal photos based on a comparison of pixel-based decision trees with object-based SVM. This comparison was carried out in order to classify the photographs. The object-based support vector machine (SVM) has a higher level of accuracy when compared to the pixel-based decision tree. Classifiers were developed by Albert et al. [11] for the purpose of classifying ethereal photographs. These classifiers were based on conditional random fields and pixel-based analysis. According to the findings of these researchers, these methods can be useful for land cover classes that span broad areas and have a consistent appearance.

## RELATED WORKS

Researchers working in areas such as further detection have been inspired to employ CNN in picture classification as a result of its success in areas like as computer vision, language modelling, and discourse recognition. CNN has been the subject of a handful of published publications for the purpose of the classification of inaccessible image detection [12–15]. This section provides a concise overview of a handful of these works, focusing on the conclusions they reach as well as the constraints they face. Sun et al. [16] offered a computerised demonstration for feature extraction and classification with classification refining. The demonstration utilised a combination of random timberland and CNN. It's possible that their combined model will perform better than the separate models' results (86.9%) and have a greater level of accuracy. A model that was built by Akar [1] and was based on Revolution Timberland and OBIA was used to classify aerial photos. Their experiments demonstrated that their technique performed better than delicate AdaBoost, with individual accuracy ratings of 92.52% and 91.29% respectively. The results were compared to those of AdaBoost. Calculations for deep learning based on CNN were established by Bergado et al. [17] for the purpose of ethereal photo classification in high-resolution urban ranges. They used data from optical groups along with ground truth maps and advanced surface models. According to the findings, CNN performed better than traditional classification approaches that are based on the extraction of textural qualities when it came to learning discriminatively relevant highlights, which ultimately resulted in accurately categorised maps. Connecting CNN was one of the steps that Scott and his colleagues [13] took in order to build land cover maps from high-resolution photographs. Cheng et al. [12] and other researchers employed CNN as a classification approach in order to interpret scenes from airborne photos. Moreover, CNN was utilised by Yao et al. [15] and Sherrah [14] in order to semantically categorise airborne photographs. The purpose of this study is to investigate the development of a CNN model for classifying aerial orthophotos into common arrival cover classes utilising regularisation approaches such as dropout and clump normalisation (e.g., street, building, water- body, prairie, fruitless arrive, shadow, and thick vegetation). The primary objective of the project is to carry out a variety of tests with the intention of determining how CNN models and hyperparameters influence the accuracy of arrive cover categorization when using ethereal photos as the data source. In order to develop models that have a high level of generalisation capability, the objective is to discover the architecture design and hyperparameters used by the CNN show.

## METHODOLOGY

METHODOLOGY

The dataset, preprocessing, and technique for the suggested CNN demonstrate counting the network engineering and preparing strategy are shown in this part.

**Preprocessing and Dataset**

(i)Dataset- Based on the area's diversity of land cover, a pilot area was chosen to test the current research. The research area is in Malaysia's Selangor province (Figure 1).

(ii) Preprocessing

(a) Geometric Calibration—Geometric calibration was necessary to correct the geometric errors since the orthophoto was captured by an aerial laser filtering (LiDAR) framework. At this step, the data were modified in accordance with ground control focuses (GCPs) gathered in the pitch (Figure 2). 34 GCPs were identified from easily recognisable sites (i.e., street convergences, corners, and control lines). ArcGIS 10.5 programme was depleted by the geometric correction. The geometric correction process involved locating the orthophoto's change foci, applying the least squares change algorithm, and determining the method's accuracy. Inside the zone, the designated focuses were evenly spaced out. After that, it was connected to evaluate the fundamental coeffi- cients for the geometric transformation process using the smallest square approach (Kardoulas et al., 1996). The polynomial equations were used to unravel for X, Y arrangements of GCPs after the smallest square arrangement and to calculate the residuals and RMS errors between the source X, Y facilitates and the retransformed X, Y facilitates.

(b) Normalization - In order to prevent anomalous slopes, a z-score normalisation was attached to the pixel values of the orthophotos because the ethereal orthophotos contain integer advanced values and the initial weights of the CNN model are arbitrarily selected within 0-1. This phase is crucial since it advances the enactment and optimises the angle descent (LeCun et al., 2012).

$$X' = \frac{(X/\max) - \mu}{\sigma}, \qquad (1)$$

where max is the greatest pixel esteem within the picture, μ and σ are the cruel and standard deviation of X/max, respectively, and X′ is normalized information.

**The Proposed Approach**

**Diagram**- Digital values with the m, n, and d prefixes are used to construct an orthophoto. These prefixes stand for the image's width, length, and depth, respectively. The objective of a classification demonstration is to give a name to every pixel in the image while being provided with a set of training cases and the names that correspond to the ground truth. All of the standard algorithms for classifying things do their part to achieve this goal by making use of the surprising data (image pixels across several groups). Just prior to the process of classification, a few additional methods, such as object-based image analysis (OBIA), separate the input image into a number of distinct, similar-looking groups that come into contact with one another. This strategy improves the classifier's performance by using extra features, such as spatial information, shape information, and texture information. However, there are a number of problems with both the pixel-based system and the OBIA system, the most notable of which being dot commotion in the first approach and segmentation optimization in the OBIA system. In addition, high classification precision can only be accomplished using any method if the highlight design and band selection are done with extreme care. Recently, classification methods that make use of photo patches and deep learning algorithms have been created in an effort to overcome the problems that have been outlined above. CNN is commonly used as one of the strategies. As a consequence of this hypothesis, a classification approach has been proposed for the purpose of classifying extremely high-resolution ethereal orthophotos. This approach is founded on CNN and spectral spatial highlight learning. The parts that follow detail the suggested programme in addition to its components, which include the CNN principles, the organisational engineering, and the preparatory strategy, among other things. Calculation 1 provides a demonstration of the proposed classification through the use of pseudocode. Before constructing the CNN model, we constructed a number of different configurations and ran those configurations through a series of experiments. At that point, utilising a few other measurable precise measurements, such as overall accuracy, the Kappa list, and per-class exactnesses, we were able to define the ultimate model with the most effective hyperparameters and engineering.

Convolutional neural systems, also known as ConvNets, are a form of artificial neural system that mimics the architecture of the human visual cortex. These systems, also known as CNNs, use a local receptive field and shared weights. LeCun and his colleagues all contributed to the presentation that was [18]. Figure 3 depicts a typical convolutional neural network with convolutional max pooling processes. CNN is effective for analysing images, recordings, or information when applied within the framework of n-dimensional clusters that contain a spatial component. Because of their unique quality, further sensing and picture categorization can be accomplished using them successfully. A typical CNN engineering consists of several layers, some of which include convolution, pooling, totally associated (thick), and calculated regression/Softmax. These are just a few of the layers. Other layers, such as dropout and clump normalisation, may also be utilised in order to prevent these models from becoming overfit and to improve their capacity to be generalised. The final layer is determined by the nature of the problem; for example, a computed relapse (sigmoid) layer is generally used for problems that include twofold categorization when it is appropriate to do so. Instead, a Softmax layer is utilised as a means of resolving issues that arise from the classification of several classes. In these models, every layer has its own distinct mode of operation and is point-based. For example, the purpose of the convolutional layers is to generate include maps by employing convolutional filters, which have the potential to learn high-level highlights that enable the properties of the image to be exploited. The yield of these layers will then go via a nonlinearity, such as a ReLU, after that is complete (corrected linear unit). When it comes to cluster information, neighbouring data groups are frequently associated, and local picture insights are not dependent on geography [19]. Expanding layers, which are often referred to as subsampling, are utilised in order to combine highlights that are semantically equivalent into a single highlight. In highlight maps, the approach of computing the maximum of a local fix of units is one of the most common and popular subsampling methods.

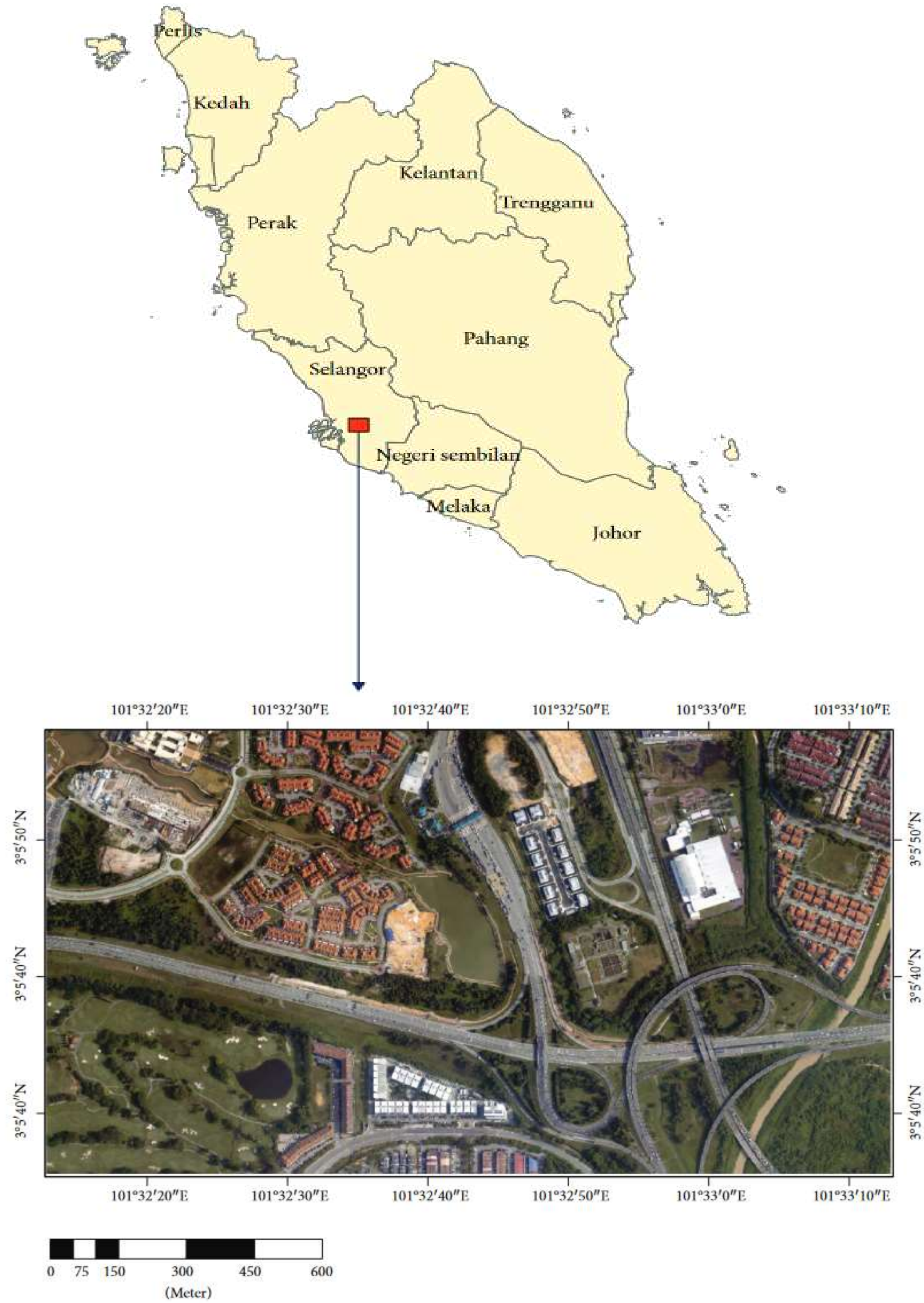


**Figure 1: The study area location map**

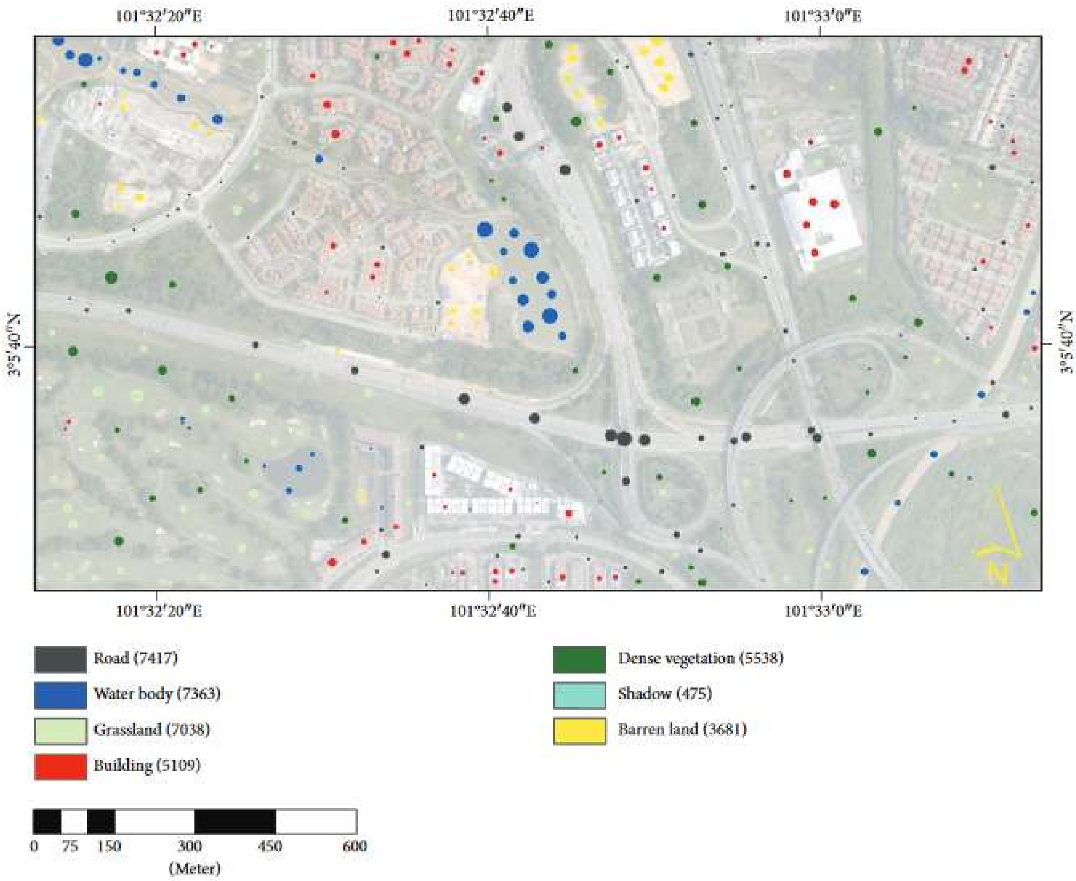


**Figure 2 shows the ground truth samples that were taken over the study region and manually chosen for seven different land cover classes, including road, water body, grassland, building, thick vegetation, shadow, and barren terrain.**

There are further methods of pooling, such as the averaging-max pooling and the stochastic pooling. It is common practise to stack several convolutional and subsampling layers, as well as thick layers, a Softmax or calculated relapse layer, and a few deep layers in order to forecast the names of each pixel in an image.

**(iii) Organize Engineering**- The CNN model was constructed using a single convolutional layer, a max pooling operation, bunch normalisation, and two dense layer classifiers. Moreover, the model was given a bunch normalisation (Figure 4). This design resulted in 3527 add-up parameters, 96 of which are unable to be trained. Both the pooling size and the convolutional bit count remained at their previous levels throughout the maximum pooling layer: 2.2 and 3.3 respectively. Dropout was performed within the convolutional layer, and the primary thick layer was set to 32 photos with a drop likelihood of 0.5 so as to avoid overfitting. This was done in order to maintain a safe distance from the problem of overfitting. Underneath the Keras system and Tensorflow back-end, the entire procedure was executed on a computer with a Core i7 processor running at 2.6 GHz and a memory smash (Slam) of 16 GB. Random selection was used for the preparation of sixty percent of the tests, and forty percent of the tests were chosen for actual testing. In general, the exactness (OA), the average accuracy (AA), the Kappa coefficient (), and the per-class accuracy (PA) are the metrics that are utilised to measure how effectively the CNN classification strategy was put into practise (Congalton and Green, 2008). The layers of the model are broken down and summarised in Table 1.

(iv) Getting Ready to Give the Presentation: Calculations using backpropagation and stochastic slope descent were employed in the preparation of the CNN show (SGD). It does this by using the backpropagation error of the minibatch to approximate the error of all of the preparation tests. This speeds up the weight upgrading cycle and allows for a smaller backpropagation error, which speeds up the joining of the entire model. In order to lower the CNN's misfortune function (J), which is also referred to as categorical cross entropy, the following optimisation was carried out:

$$J\left(X', W, b, \theta\right) = -\frac{1}{N}\left[\sum_{i=1}^{N}\sum_{j=1}^{k} 1\left\{y^i = t\right\} \cdot y_t^i\right], \qquad (2)$$

where W and b are parameters of the CNN, X′ is a normalised highlights, is a parameter of the Softmax layer, N is the number of tests, k is the number of arrive cover classes, and yi = y I 1, y I 2,... the Softmax classifier (3), where y I t speaks to the plausibility of the ith sample label being t and is calculated by (3).

$$y_t^i = \frac{\exp\left(\theta_t^T c\right)}{\sum_{j=1}^{k}\exp\left(\theta_t^T c\right)}. \qquad (3)$$

Amid back engendering, (4) are adjusted to overhaul W and b in each layer, where λ is the energy which help accelerate SGD by including a division of the overhaul esteem of the past time step to the current upgrade esteem, α is the learn- ing rate, ∇W and ∇b are the slopes of J · with regard to W and b, individually, and t fair stands for the number of epoch amid SGD:

$$\begin{aligned} W_{t+1} &= W_t - \lambda V_t - \alpha \nabla W, \\ b_{t+1} &= b_t - \lambda U_t - \alpha \nabla b. \end{aligned} \qquad (4)$$

**(v) Assessment**- This consider employments a few measurable accuracy measures to assess diverse models and compare them under different exploratory arrangements. These metrics are by and large precision (OA), normal exactness (AA), per-class accuracy (Dad), and Kappa record (κ). They are calculated using the taking after conditions [20]:

$$\begin{aligned} \mathrm{OA} &= \frac{\sum D_{ii}}{N}, \\ \mathrm{AA} &= \frac{\sum_1^m PA_m}{m}, \\ \mathrm{PA} &= \frac{D_{ij}}{R_i}, \\ k &= \frac{N\sum_{i,j-1}^{m} D_{ij} - \sum_{i,j-1}^{m} R_i \cdot C_j}{N^2 - \sum_{i,j=1}^{m} R_i \cdot C_j}, \end{aligned} \qquad (5)$$

where ∑D ii is the full number of accurately classified pixels, N is add up to number of pixels within the blunder network, m is the number of classes, Dij is the number of accurately classified pixels in push i (within the inclining cell), R i is the entire number of pixels in push i, and C j is the full number of pixels in column j.

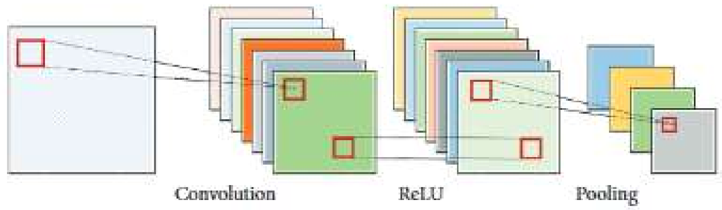


**Figure 3: Illustration of typical layers of a CNN**

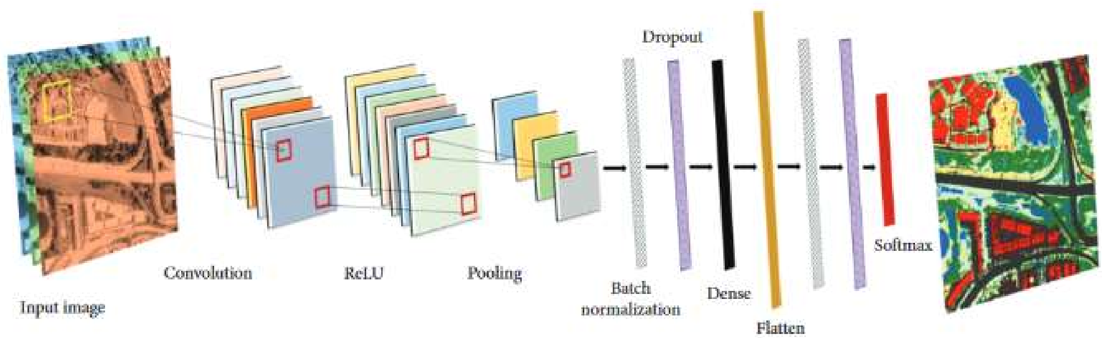


**Figure 4: The architecture of the proposed CNN for aerial orthophoto classification**

**Algorithm 1:** CNN for orthophoto classification
**Input:** RGB image (*I*) captured by the aerial remote sensing system, training/testing samples (*D*)
**Output:** Land cover classification map with seven classes (*O*)
*I*, *D*, *O*
**Preprocessing** (Section 3.1.2):
**calibrate** *I* using the available 34 GCPs
**normalize** pixel values using Eq. 1
**Classification (CNN)** (Section 3.2.2 and Section 3.2.3):
**for** Patch_x_axis:
  **initialize** sum = 0
  **for** Patch_y_axis:
    **calculate** dot product(Patch, Filter)
  result_convolution (x, y) = Dot product
**for** Patch_x_axis:
  **for** Patch_y_axis:
    **calculate** Max (Patch)
result_maxpool (x, y) = Dot product
**update** F = max(0, x)
result_cnn_model = trained model
**Prediction:**
apply the trained model to the whole image and get *O*
**Mapping:**
**get** the results of prediction
**reshape** the predicted values to the original image shape
**convert** the array to image and **write** it on the hard disk

**Algorithm 1: The Pseudo code of the proposed CNN developed for land cover mapping using aerial images**

| Layer (type) | Output shape | Number of parameters |
|---|---|---|
| Input | (None, 3, 7, 7) | 0 |
| 2D convolution | (None, 1, 5, 32) | 2048 |
| Max pooling | (None, 1, 2, 16) | 0 |
| Batch normalization | (None, 1, 2, 16) | 64 |
| Dropout | (None, 1, 2, 16) | 0 |
| Flatten | (None, 32) | 0 |
| Dense | (None, 32) | 1056 |
| Batch normalization | (None, 32) | 128 |
| Dropout | (None, 32) | 0 |
| Dense (Softmax) | (None, 7) | 231 |

**Table 1: The summary of the CNN model layers**

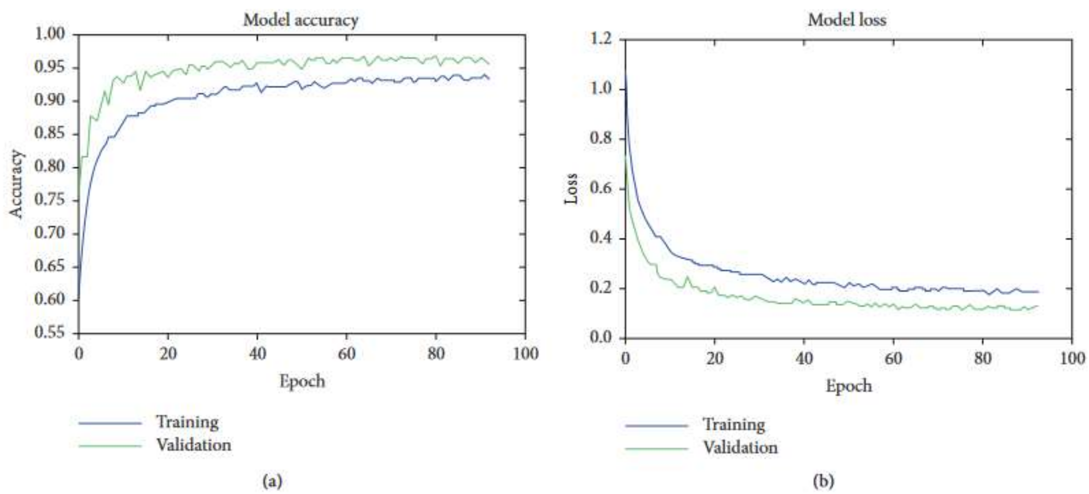


**Figure 5: Performance of the CNN model with optimum parameters set, (a) model accuracy and (b) model loss for 93 epochs (early stopping)**

| Class | PA |
|---|---|
| Road | 0.971 |
| Waterbody | 0.944 |
| Grassland | 0.972 |
| Building | 0.995 |
| Dense vegetation | 0.999 |
| Shadow | 0.894 |
| Barren land | 0.980 |

**Table 2: PA of the CNN model**

## CONCLUSION

According on the findings of this research, a classification approach for aerial photographs that utilises CNN and spectral-spatial include learning is recommended. The show that is being offered appears to change the training productivity and generalisation capacity by applying advanced regularisation procedures such as dropout and group normalisation. If these models are utilised in conjunction with other methods, such as preprocessing (geometric calibration and include normalising), as well as sensitivity analysis, there is a possibility that they will be successful in classifying the data that has been provided. A highlight extractor is provided by the CNN programme, and with the help of training examples, a classifier can be constructed from beginning to end. The association- and intraclass-level complexity that exists inside the scene can be effectively managed by the arrangement engineering. The top model achieved a 4% improvement in performance compared to the conventional CNN example across all three precision pointers (OA = 0.973, AA = 0.965, and = 0.967). The proposed show's efficiency for further detecting datasets on small and medium scales was validated by the little amount of time it required for preparation (124 seconds). The primary objective of any future work should be to scale this architecture to accommodate large remote detecting datasets as well as other types of data sources, such as satellite photos and laser checking point clouds.

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