VISWAM PUBLICATIONS

Journal of Computer Science & IT Research and Review

https://viswampublications.com/journals/index.php/jcsitrr



LENET-CNN FOR FEATURE EXTRACTION AND ACCURATE CLASSIFICATION OF REMOTE SENSING MULTI-SPECTRAL SATELLITE IMAGES USING MACHINE LEARNING

[1]**D.Suganya** ResearchScholar, PG&Research Department of Computer Science, Christhu Raj College (Affiliated to Bharathidasan University),

[2]**Dr. R.Sugumar** Professor& Director, Research Advisor, PG& Research Departmentof Computer Science ,Christhu Raj College (Affiliated to Bharathidasan University)

ARTICLE INFO

Received : 15.03.2025
Revised : 28.05.2025
Accepted : 12.08.2025
Published : 26.09.2025

Corresponding author:
D.Suganya
sugisats@gmail.com

Keywords:
Machine Learning,
Remotesensingimages,
Featureextraction,
Classification,
Hybrid LeNet and
Convolution,
Neural Network (CNN) and
High accuracy.

ABSTRACT

For a variety of uses, such as disaster relief, engineering, law enforcement, and environmental monitoring, satellite imagingis strongand indispensable. Conventional techniquesfor object detection and categorization are imprecise and unreliable. Applications that automatically classify and detect items in photos are needed to address this problem. Image processing is performed to extract or enhance images with high quality. This study suggested Machine Learning (ML) techniques that improve the classification of remote sensing photos and identify objects to make the images more convenient. A subset of artificial intelligence (AI) called machine learning uses information from past events to learn and adapt how a computer program behaves. Color and image pixel values are grouped into consequential categories as part of the multi-spectral satellite image categorization process. Accurate satellite image classification and feature extraction from remote sensing images is accomplished using a hybrid approach that combines the LeNet and Convolution Neural Network (CNN) algorithms. The concept of a neural network to recognize patterns much like human brains is employed. The proposed system uses a hybrid algorithm to achieve feature extraction and object detection through machine learning techniques .The dataset includes a variety of large-scale photosand collections of satellite images gathered from the Kaggle database, which is the largest community in the world offering a data platform for learning data science. Color, Texture, and structure are the three main categories from which the hybrid techniques are employed to extract the feature. The best optimizer of LeNet helps separate hyper spectral images based on their shape and texture. CNN can classify land cover types with higher accuracy, especiallyin mining areas. CNN function analyse data and recognize patterns for accurate classification of images.Semantic segmentation of a remotely sensed image in the temporal, spatial, and spectral-domain is an essential pre-processing step where different classes of objects like water bodies, industrial, crops, pasture, and roads are localizing by a boundary. The results of the inquiry show that the suggested Hybrid LeNet and Convolution Neural Network (CNN) algorithm provides high-accuracy object detection and feature extraction through machine learning techniques.

This article is licensed under Creative Commons Attribution-Non-commercial 4.0 International License.
Copyright©2025 Author(s) retains the copyright of this article. DOI:

I. INTRODUCTION

The provision of both qualitative and quantitative geographical data by satellite photos is crucial in lowering the complexity of fieldwork and inquiry timeframes. Receiving photos from data centers, the satellite photographs are gathered at regular intervals and grow exponentially over time. Although a satellite image is not complicated, analysts must make numerous selections while classifying remote-sensing satellite images.

This method explains how to use sensing photos, analyze metropolitan areas to identify different land regions, use spatial data mining, and examine different plant kinds, including farmland and forests. In several domains, including natural language processing, agricultural computer vision, and medicine, deep learning has experienced remarkable expansion. In contrast to traditional deep learning, deep learning can learn robustly and make better use of sensing picture datasets for feature extraction.

According to the practicability perspective, deep learning is becoming a more important area of study for many scholars. To categorize numerous satellite photos, this paper concentrated on optimizing various parameters utilizing CNN of deep learning. The CNN classifier is utilized for object classification after LeNet is used for feature extraction. As seen in Fig. (2), the suggested system uses a hybrid LeNet-CNN algorithm to accomplish goal identification, feature extraction, as well as classification utilizing deep learning methodologies.

II. RELATED WORKS

Athira M.V et al [1] Over the past year the object detection has been dealing with extreme development. The onset of deep learning has boosted high performance and accuracy in improving several systems. This survey developed several works in the image detection field and classification using ML, deep learning, and object detection-based night vision applications. The paper classified the object detection by using image classification performance to separate the infected regions with better high accuracy.

Muthu Krishnammal et al [2] authors have carried out to investigate intensive research on abnormalitiesthere inthe structure of thebrainthe detectionoftumor typesbasedonthe imageof the brain is statistically extracted from the medical images of features. Using MRI images for detecting tumors is traditional buttheaccuratelocation and quantitysize of the tumor is aclinical challenge for the further treatment process. The proposed system includes three stages for tumor detection that are feature extraction, segmentation of images, and tumor segmentation. The deeplearning techniquesare used for feature extraction through wavelet transform with multiresolution techniques.

Rahul Neware et al [3] Geospatial data addresses the higher resolution of remote sensing data anditworksindifferentfieldsfor example,forests, waterresources,landcover,geosciences, disastermanagement, soil,andenvironment. Someimage processingtechniquesareappliedto getthe requireddata from the satelliteimages. The essentialpart ofimage processingisthe classificationand segmentation of remote sensing images into their land cover area. This survey used the supervised method,unsupervisedmethod,andobject-orientedclassificationtodiscovertheland-coveredarea by using classification techniques through satellite images.

III. PROPOSED METHODOLOGY

A) DATASET COLLECTION

TheKaggledatabase,thelargestcommunityintheworldofferingadataplatformforstudying data science,iswhere satelliteimagesaregathered.Classifyingsatellite photosisa traditionalmethod of extractinginformation andidentifying objectsbypixel range from a vast numberof sensor images.

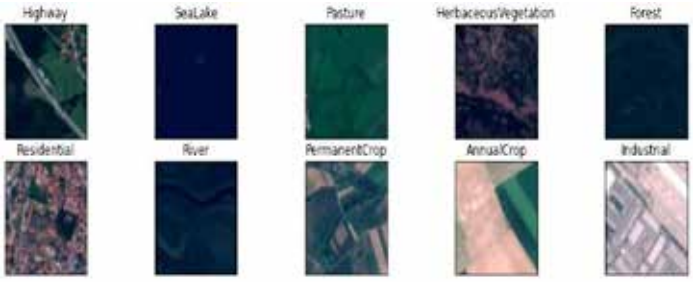
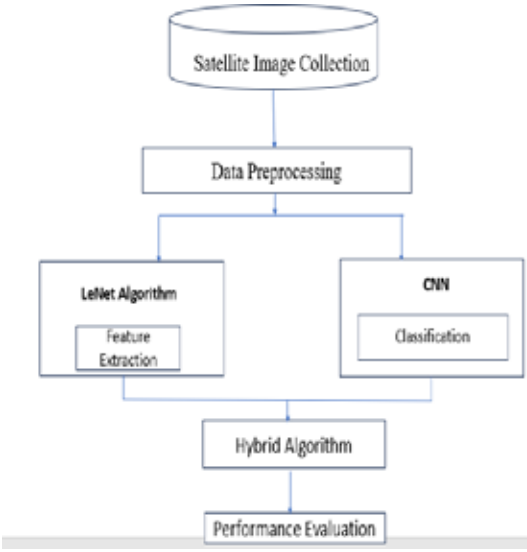


Figure1:Satellite Images dataset with 8x8 pixel range

As seen in Fig. (1), various image types with various pixel counts were used as input images for datasets. Remotesensingphotos fromseveral categories wereused inthestudy, and theyincluded a wide range ofqualityandsize (e.g., 300x280,345x500,500x414,etc.)[4]. Few ofthe imagesinthe collection are of flawless quality, however, some have a background that is constant while othershave a background that is clustered.

DATA PREPROCESSING

The data pre-processing stage is a significant phase for sharinginput images with similar properties. The first stage was the training phase the images are processed through a starting method based on feature vector extraction depending on deep



learning techniques. The dataset applied in our model has distinct colors for each image preprocessing converting all imagesinto 256*256 uint8 3 bands for the red, green, and blue channels. In the data pre-processing stage all input satellite images are resizing the image size with the same dimensional region. So the testing phase can classify the images into color normalization by reducing invisible or irrelevant bands from the SAT dataset. Following the conversion of photos into grayscale, all of the dataset's images are prepared for the subsequent feature extraction process, which adds each satellite image to the trainingand testingsets.

Figure2: Proposed block diagram

B) LeNet USED FOR FEATURE EXTRACTION

The impact of attributes taken from the input satellite dataset of training images determineshowwellremotesensingimagecategorizationworks.Asseeninfig(3),thefeaturethatwastaken

from the photos offers a high-level procedure utilizing LeNet algorithms. Using the LeNet technique, the feature extraction is separated into three groups: texture, structure, along with color, as explained in the approaches.

i) Structure-Based Feature Extracted

Self-Similarity(SSIM):AsetofpointsataphaseinboththeXandY-directionsofeightpixels wasused to analyze the SSIMstructure. Each descriptor'ssatellite picture is gainedbycalculatingthe correlation map of a 9×9 pixel area in a window with a radius of 4 pixels. Four angular and radialbins are extracted from the image to provide 12 dimensions of descriptor vectors.

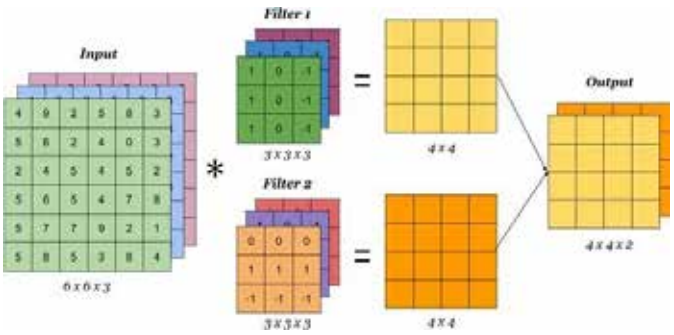


Figure3: Feature extraction based on LeNet

Geometric Blur (GB):One of the aspectsthat are taken out ofthe satellite photosisthe spatial variation of Gauss kernels and the convolution of the image. GB explains how to extract the three channels, each of which has vectors with 68 dimensions.

ii) TextureBasedFeature Extracted

Local BinaryPatterns(LBP): Thisiscalculated utilizing8samplepointsonacircle'sradiusof one pixel,and it isalsotakenfroma normal patchsize of 16× 16 pixels. It is specified asinvariantto process rotation and grayscale. Schmid Filter Bank (SF): The 13 dimensions of each pixel vector in the set of invariant filters rotate in response to the dimensionality reduction of each image.

iii) Color Based Feature Extracted

ColorHistogram: Thecolorspaceisthemajorfeatureto extracttheimagesmore accurately it is defined as a red–green–blue (RGB) channel to calculate the histogram into all RGB channelswith 40bins. Subsequently, the three color channels defined 120-dimensional Colorhist and concatenated separate histograms. The regular grid is used to define the feature extraction, which yields 20 × 20 pixels with a 10-pixel overlap phase.

Color Pool and Hue: The photos were divided into 4 x 4 non-overlappingrectangular sections using the color mean concatenated feature. The mean color of the R, G, and B channels is found and concatenated with each channel to determine the pixel value in each area of the image.

The texture features the first process is filtering and image using above mentioned extraction to calculate the average range of all pixels on the regular grid size of 20 × 20 pixels. All the stated features are lastly quantized into the feature extraction process by using LeNet techniques and the histograms are counted based on the pixel value and then used for the classification methods.

C) IMAGE CLASSIFI CATIONUSINGCNN

The satellite images are used to extract the feature and based on the features the CNN algorithm of a deep learning process for classification.CNN is primarilyused to extract features and classify objects from the satellite images as shown in Fig (4). Various image classification examples are Highways, Rivers, Forests, Industrial lakes Etc.

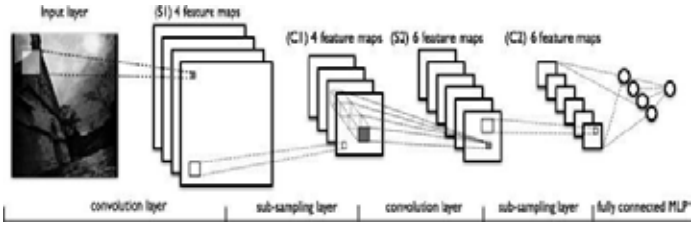


Figure4: CNN Architecture for Layer Processing

Learningfor detectingblobandedge features is the first layer of theCNN progression and these actual features are treated by a deeper layer [9]. It is utilized for classification or recognition tasks at theentire connection layer if the initial features are paired with additional high-level features. Commonly, a CNNmostlycontains3significant portionsfirstconvolutionlayers, secondpooling layers, as wellas finallyfullyrelated layersas shown in fig (4). In convolution neural layersthe input mapsare involved to form the output feature maps with learnable kernels and are activation functions put through subsequently. The bias of the j^{th} feature map in the m^{th} layer is (b_m, j), and the kernel position (h, w) is the one corresponding to the m^{th} featuremap in the (m -1)th layer. These convolution layers reduce the number of parameters by establishing a weight-sharing mechanism within related feature maps. The CNNisusedto classify the imagethrough processing differentty pesoflayersposition (h,w)ofthe kernel that is linked to the m^{th} fea-

ture map in the (m -1)th layer correspondingly and (b_m, j) is the biasof the jth feature map in the mth layer. These convolution layers reduce the number of parameters by establishing a weight-sharing mechanism within related feature maps. The CNN is used to classifythe image by processing different types of layers as shown in Fig (5).

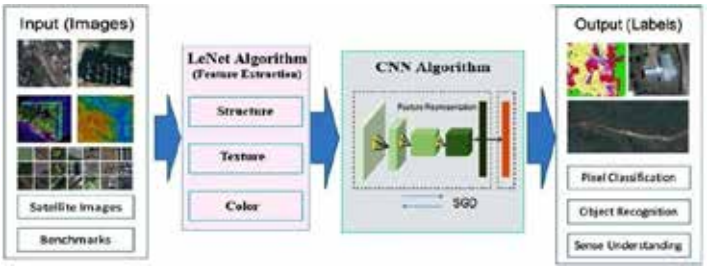


Figure5: Architecture of overall research methodology

There are two advanced techniques used to classify the image accurately by using deep learning techniques [9]. There is a versatile collection of image datasets that are classified based on the extracted features of a classification system. The Hybrid method of LeNet-CNN is employed for extracting the features and segmenting the images more efficiently with the help of pixel classification.

V. CONCLUSION

Using a dataset of natural remote sensing photos, which contains approximately1000 training images pertinent to the category, this study investigated the convolutional neural network. The best parameter of the suggested architecture allowed us to attain the highest classification accuracy. There hasbeen athorough comparison of the different deep-learningapproaches. To achieve high accuracy, deep learning algorithms were applied during the satellite image classification training and testing phases. The CNN algorithm on the Layer network is used to classifythe images based on the features that have been gathered usinga varietyof methodsandthe LeNet algorithm. The Hybrid LeNet-CNN system uses deep learning techniques to identify and categorize the satellite photos. Lastly, the classification of satellite images with high accuracy is evaluated quantitatively in this work using metrics including precision, recall, and F1 score.

REFERENCE

[1] AthiraM.V andDiliyaMKhan,“Recent Trends onObject Detectionand ImageClassification: A Review”, IEEE published 18 September 2020, DOI: 10.1109/ComPE49325.2020.9200080.

[2] Muthu Krishnammal P, and S. Selvakumar Raja, “Deep Learning Based Image Classification and Abnormalities Analysis of MRI Brain Images”, IMICPW IEEE Xplore: 19 December 2019

[3] Rahul Neware and Amreen Khan, “Survey on Classification Techniques Used in Remote Sensing for Satellite Images”, IEEE: ICECA 01 October 2018.

[4] Subhankar Roy, Enver Sangineto, Nicu Sebe, and Begüm Demir, “Semantic-Fusion Gans for Semi-Supervised Satellite Image Classification”, IEEE International Conference, 06September2018.

[5] Farid Melgani, and Lorenzo Bruzzone, “Classification of Hyperspectral Remote Sensing Images With Support Vector Machines”, Vol. 42, No. 8, August 2018.

[6] K He, X Zhang, S Ren, and J.Sun, “Deep residual learning for image recognition”, in The IEEE CVPR, June 2016.

[7] Li Y, Tao, C Tan, Y Shang, and K Tian, “Unsupervised multilayer feature learning for satellite image scene classification”. IEEE Geosci Remote Sens - 2016 Lett. 13(2), 157–161.

[8] Zheng, X Sun and Hongqi Wang, “Automatic Annotation of Satellite Images via Multi-feature Joint Sparse Coding With Spatial Relation Constraint”, IEEE, VOL. 10, 2013 NO. 4, JULY 2013, pp.652-656.

[9] Imdad A. Rizvi, Komal M Sukre, and M M Kadam, “Image Classification of High-ResolutionSatellite Imagery Using Deep Learning Approach”, IRJAES: 2017- Vo 2(1), 84-86.

.

[10] C.Szegedy,W.Liu,Y.Jia,P.Sermanet,S.Reed,D.Anguelov,D.Erhan,V.Vanhoucke,and

A.Rabinovich, “Goingdeeperwithconvolutions,”inTheIEEE-Conference,June 2015.