

EFFICIENT DETECTION AND CLASSIFICATION OF AGRICULTURE CROPS FROM REMOTE SENSING SATELLITE IMAGES

Submitted in partial fulfilment of the requirements for the award of Bachelor of
Engineering degree in Electronics and Communication Engineering

By

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Inti Yaswanth Pavan Sai** (Register No: 37130161) who carried out the project entitled **EFFICIENT DETECTION AND CLASSIFICATION OF AGRICULTURE CROPS FROM REMOTE SENSING** under my supervision from November 2020 to April 2021.

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I **INTI YASWANTH PAVAN SAI (37130161)** hereby declare that the Project Report entitled EFFICIENT DETECTION AND CLASSIFICATION OF AGRICULTURE CROPS FROM REMOTE SENSING SATELLITE IMAGES done by me under the guidance of **Dr.B.RAJASEKAR B.E, M.TECH, Ph.D** at Sathyabama institute of science and technology is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in ELECTRONICS AND COMMUNICATION ENGINEERING.

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ABSTRACT

Classification and recognition of crops is an important prerequisite for crop yield estimation and crop growth monitoring. Rapid and accurate acquisition of crop type, spatial distribution and area information can provide basic basis for crop planting structure optimization and structural reform of agricultural supply side. In recent years, hyper-spectral remote sensing has been able to fine classify crop types and varieties and obtain spatial distribution maps and planting structure information of crops by virtue of its many bands, abundant spectral information and sensitivity to small spectral differences among ground objects. Real-time monitoring of agricultural crops is increasingly important because of the involved huge economic impact. The automatic identification of crops, as early as possible during the agricultural season, is an important issue supporting agricultural policies. In this context, the objective of this project is to evaluate the possibilities of remote sensing data to identify corn and paddy field crops in the early growing season.

Existing methods for solving the object recognition task usually rely on segmentation and feature extraction. One of the major challenges that many developed algorithms face is their inapplicability to other domains. Many solutions for image segmentation and classification work perfectly for one particular problem and often for one particular region with well-known seasonal changes in imagery. It must be mentioned that due to the aforementioned progress in acquisition technology and excessive resolution, image segmentation is often not of interest, and image data can be cropped into regions with fixed dimensions. For image classification, one possible way to address the problem of algorithm generalization is to utilize deep learning algorithms, for instance a convolutional neural network (CNN).

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CHAPTER 1

INTRODUCTION

Aerial and satellite imagery processing is useful for a variety of purposes, including land inventory and landscape tracking. There has been a lot of research done on imagery collection, corrections, and aerial imaging geo registration techniques. Data mining has undergone dramatic transition in recent years as a result of lower data acquisition rates and technical advancements. Images, on the other hand, have no meaning until they are understood and accurate evidence is gathered. Several methods for automating the process of satellite imagery information recovery have recently emerged, and several application areas have been targeted.

For solving the recognition problem, existing methods normally rely on segmentation and feature extraction. The inapplicability in other fields is one of the major issues facing many existing algorithms. Many picture segmentation and classification methods fit well for one issue and also for one area with well-known seasonal shifts in imagery. The above listed advances in acquisition technologies and disproportionate resolution also cause the segmentation of images to be irregular and the data can be divided into fixed-dimensional regions. One possible way to solve the algorithm generalization problem is by using in-depth learning algorithms, for example a convolutionary neural network (CNN).

The primary benefit of CNN-based algorithms is that they do not require prior feature extraction, resulting in improved generalization capabilities. CNNs have recently been demonstrated to be useful in object identification, object detection, image parsing, and scene classification. We investigate the use of a CNN for per-pixel classification of very high resolution (VHR) satellite imagery in this paper. In the last four years, there have been several reports on the use of CNNs for satellite imagery. Nguyen et al. suggested a satellite image classification algorithm that used a five-layered network and achieved high classification accuracy between 75% and 91 % using six classes: airport (78%), bridge (83%), forest (75%), harbor (81%), land (77%), and municipal (91 percent). 91

percent Hudjakov and Tamre used a network of three inner layers (two convolutional and one linear 2-classifier) to per-pixel classify terrain based on traversability (road, grass, houses, bushes) for long-term route planning for an unmanned aerial vehicle (UGV). Wang et al. also addressed a related topic. The authors combine CNN with a finite state machine (FSM) in their work to generate a road network from satellite imagery. Chen et al. used CNN to detect individual vehicles in satellite images.

In the past, CNNs have also been used for high-resolution remote sensing scene classification (HRRS) data with promising outcomes from the UC Merced Land Use dataset. The transmission of this works is carried out using a previously qualified CNN to identify the object and finish the job using a remote sensing program. Ishii et al. compared the CNN with the Landsat 8 imaging support vector machine (SVM), and found the CNN to outperform FSM. Zhang and Zhang proposed a scenario classification system for the boost of a random convolutionary network (GBRCN). The authors say a better output (with a space resolution of 1.0m) of their algorithms in UC and Sydney data sets over the known state-of-the-art algorithms (as of 27 November 2015). The problem of segmentation can include various solutions while CNNs are widely seen as a good and promising solution for object classification, thus defining the CNN's exact architecture.

Previous pixel-classifying techniques, for example, used spectral information in a single pixel from hyperspectral images of hundreds of channels of small frequency stripes to distinguish each pixel. Only the salt and pepper effects of misclassified pixels have made this pixel-based classification scheme common, and it was difficult to manage the rich information from high resolution details. More spatial detail in the pixel region to be rated has been added to the work. Contextual information was often used in order to learn how to differentiate neural network roads from those of other classes. The use of a CNN on multi-spectral data is tested on this work with a broader area up to 45 pixels, while most of the works involve adjacent pixels in a smaller region of about 10 - 10 pixels. This issue can be addressed by segmenting the image before categorizing it (using various segmentation techniques). The use of CNNs to distinguish satellite data

per pixel is adopted as a new approach.

First, we plan a CNN using an unmonitored clustering algorithm, and then we adapt this algorithm to per-pixel sorting, identification, and segmentation functions. CNN has an intriguing aspect in that it dynamically learns functional representations by unsupervised feature learning. Other applications include computer vision, speech recognition, and time series analysis. The data used in the work was a detailed city map of northern Sweden, multi-spectrally northern true spelling, numerous synthetic image bands, two near infrared belts, and a digital satellite vision (DSM) model. True ortho is a mosaic of many images that represent a true nadir rendering in an accurate, seamless 2D frame. Furthermore, the actual ortho image is precisely consistent with the DSM used. Vricon kindly provided the details.

The use of a DSM improves classification accuracy by including height details to help distinguish between similar look-alike categories like plants and dark soil. Furthermore, for lighting and color changes, a DSM invariably provides improved geometry estimation and background isolation. Measurements in a DSM, on the other hand, must be normalized since they are taken from a national rather than a local point of reference. The local terrain level is then calculated as the minimum DSM value of each non-overlapping region of the DSM using a local subtraction process. This means that $p_{w,w} = p_{w,w} - \min(p_{w,w})$, where $p_{w,w}$ is a nearby patch that does not overlap the DSM band w on the scale. In this object, we used a width of 250 pixels. For each band and the local DSM band, the normal score is then averaged.

Defining and acquiring reference data are also important issues in remote sensing. Most datasets using a pixel-level description use only a few hundred points of reference. Each pixel in the whole map is manually marked in order to verify the classifier by means of a much wider pool of validation points and to ensure supervised learning and tuning. The GUI offers the possibility of switching on and off the RGB networks, the height map, the maps and the segments. The map is divided into areas of 1000 by 1000 pixels and originated by a linear iterative clustering into 2000 lines (SLIC). Depending

on the amount of information required, the number of segments may be increased or reduced dynamically. A new segmentation button is required to calculate current marked pixels. Vegetation (10.0%), land (31.4%), roads (19.0%), construction (6.7%) and water are the classes used in this work (and their prevalence) on the marked chart done (33.0 percent).

Etiketting included the train and parking sections, but due to their low incidence, these two types were combined with routes. Accurate distribution maps are becoming increasingly important in agricultural land management in the face of rising food demands, and they are adapting to the world's growing human population. With the ongoing launch of satellites such as Landsat-8 and Sentinel-2 in recent years, crop classification based on medium and high resolution images from The lack of time resolution in a single optical satellite, especially in cloud-prone areas, has been effectively addressed from multiple sources.

GEOBIA is an effective tool for crop classification using multi-source satellite imagery. Picture analysis focused on geographical objects The basic unit of classification is geographic objects, not pixels, avoiding the salt and pepper effects of traditional classifiers like maximal likelihood, which can solve the issue of inconsistent space resolution between multisource data. In addition, with the addition of texture and shape information, object-driven classification can use more features to identify target objects. However, despite its advantages over traditional classifiers, GEOB is constrained by complexity in Segmentation of images, collection of features and algorithms in classification. Segmentation is a critical GEOBIA operation, which can have a major impact on the classification precision when deciding segmentation parameters.

While it provides additional information which is helpful for target identification, adding robust features may also produce noise or information that can have an impact on classification accuracy. Moreover, multiple classification algorithms performing significantly differently (exactitude, efficiency, and feasibility) have been proposed in GEOBIA. To fully exploit GEOBIA's potential in crop identification with multi-source satellite images, the optimal combination of segmentations, function selection, and

classification algorithms must be sought, which is the focus of the current study.

Segmentation of multi-resolution modes is the most commonly used GEOBIA segmentation process which uses a bottom-up segmentation strategy based on pair-wise combinations in the field. Size is a crucial parameter for multi-resolution segmentation. An too large size is likely to lead to under-segmentation and over-segmentation is due to an overly small scale. Testing/error which is no longer just arbitrary but time consuming is typical approach for determining the optimum scale (SP) parameter of multi-resolution segmentation. Some supervised and unchecked algorithms have been developed to quantitatively evaluate optimum SP and boost automation. Supervised methods use 'true' artifacts to estimate the reliability of segmentation outcomes and unattended methods use various heterogeneity and consistency metrics to evaluate segmentation outcomes. Since the unattended approach takes less time than the monitored method, the latter is more reliable.

Following a critical analysis of corresponding papers published in three major remote sensing reviews recently, Costa et al. concluded that image segmentation precision measurement is still in its infancy and that little regard has been given to the evaluation of relative skill of supervised and unmonitored approaches. It is difficult to perform a supervised optimum set of SP since it is difficult to calculate the differences between segmented and "initial" objects, in addition to being cumbersome and time consuming to accumulate reference objects over large areas. As a result, studies determining the capacity for gathering reference objects from large-scale representation fields can minimize time while maintaining accuracy.

Object-based classification can provide dozens or hundreds of results. The Hughes effect occurs when a large number of features are used to train classification models, resulting in poor classification performance. As a result, determining the importance of features and selecting the best subsets for classification may be beneficial. The optimum function subset was created using a variety of metrics such as variance, chi-square, relief-F, and correlation, while machine learning algorithms such as random

forests (RFs) may have differing meaning, which is useful for picking features. When a small aspect is combined with other features, though, it may have a significant impact on classification accuracy. With this in mind, it would be more appropriate to judge a feature subset's effectiveness based on its classification accuracy. It's also worth remembering that determining the accuracy of all feature variations is challenging due to the enormous computational effort and time involved. The best feature subset is then screened for operational reasons using a series of quest approaches. However, few studies have evaluated the efficacy of such feature selection techniques, especially for GEOBIA crop identification using multi-source satellite imagery.

1.1 Study Area

Xinghua County is a study center in Jiangsu Province, East China. It covers an area of 2353 square kilometers and has a population of approximately 1.5 million people. Within the subtropic monsoon climate zone, Xinghua County has an average annual temperature range of 14 °C to 15 °C and an annual precipitation of approximately 1040.4 mm. The region's relatively flat topography and mild, humid climate support aquaculture and agriculture, making it one of China's major food production areas.

Paddy rice is the main summer crop, while winter wheat (*Triticum aestivum* L.) and oleaginous rape are the main winter crops (*Brassica napus* L.). Green onions can be harvested three to four times a year and are grown all year.

1.2 Image Acquisition and Preprocessing

In the sense of Xinghua, only satellite images with a cloud-free footprint were downloaded for the current review in order to obtain adequate clear sky photos covering the primary phenological stages of the crops under study. In this regard, only 5 images from the multisource and two images from the Multispectral Instrument Sentinel-2A (MSI), two images from the Landsat-8 Operational Land Imager (OLI), and one image from a large view GF-1 fulfilled this criterion. On 28 February and 29 April 2017, Landsat images were purchased, and on 15 March and 18 May 2017, the GF-1 image was purchased. These photos can collect useful phenological information on wheat

winter, olive rape, and green onion in the study area from December to May, to be used as classification to distinguish between these crops. These photographs are now available for purchase.

Sentinel-2 MSI is one of the five sister missions of the European Commission and ESA Copernicus Initiative, and the user community has free access to images from this satellite through the Scientific Data Portal of the ESA. In the top of the atmosphere reflectance (TOA) the Sentinel-2 images are given as Level-1C. Using ESA's Sen2Cor atmospheric corrections tool, converting to the BOA reflectance in order to achieve Level-2A can be applied. The atmosphere correction model of the Sen2Cor relies on sensor and solar geometry-based features, soil lifting and atmospheric parameters. Only visible, close infrarouge (VNIR) and shortwave infrarouge strip (SWIR) are used in this analysis.

Landsat-8 images are used in this study. GF-1 WFV data is available from the Chinese Satellite Resource Data and Application Center (CRESDA). Data from the GF-1 WFV provide four spatial resolution bands in the 16-metre VNIR scale. The China National Space Administration's GF-1 satellite is the first of a series of high-resolution optical earth observation satellites (CNSA). It consists of four overlapping wide-view cameras (WFVs) with a swath of 830 km.

To convert raw Landsat-8 and GF-1 optical digital numbers into surface reflection, this research analysis used the 6S (second satellite spectrum simulation) atmospheric correction model[58]. The 6S is a cutting-edge radiative transmitting code that simulates a composite atmosphere-surface system reflecting solar radiation under a wide range of atmospheric, spectral, and geometric conditions. The GF-1 image was then ortho-rectified using the RPC model. After that, there's the GF-1 model. RPCs are a compact ground-to-image geometry representation that allows for photogrammetrical processing without the need for a physical camera model.

All RPCs were provided together with the raw GF-1 WFV image in a “.rpb” file.

Geometry was conducted after atmospheric correction to ensure pixel conformity to images from different sources, and the other images were captured using a Sentinel-2A MSI image (acquired on 29 April 2017).

1.3 Ground Reference Data Acquisition

Following segmentation, sample collection was carried out. Based on a random selection strategy, a total of 2025 objects were chosen to serve as samples, including 649 winter wheat objects, 230 rape objects, 176 Green Onions, and 970 objects, from satellite and high-resolution images, as well as knowledge from field studies (including data on crop categories, location, distribution, and environment), in a visual interpretation. The distribution of soil samples is shown in this diagram. 70% of the total samples per class were used in a stratified random study to check the selection and classification of characteristics. The remaining 30% was used to ensure that the random samples were correct.

1.4 Methodology

The image segmentation program was used. The Python language along with the GDAL and the Scikitlearn library have been employed for the selection, removal of features, and classification algorithms of the machine's segmentation scale. GDAL is used for reading and writing the data and Scikit-learn has been used in the removal of functional algorithms and classification algorithms for machine learning.

1.5 Image Segmentation

The program distinguishes the two highest resolution Sentinel-2A images in this study. The segmentation is built on the previously described multi-resolution segmentation algorithm. Users must define three main parameters in eCognition depending on project requirements: the scale parameter S, the form/color parameter ws form/color, and the

compact/smoothness parameters w_{compt} / w_{smooth} . Because of the fragmented and uneven croplands, the types of different crop areas are not so different. As a result, we prioritized spectral features over formal features in image segmentation. While the cumulative number of w_{shape} and w_{color} could be 1.0, they were set to 0.1 and 0.9 in the current study. In a related way, the values of w_{compt} and w_{smooth} must be 1.0, but in order to obtain equal importance for those parameters in image segmentation, they were set to 0.5. As a result, the only parameter that needed to be tweaked was the distance.

Three regions were selected for the testing facility in order to obtain the reference objects used to identify the scale parameter, representing areas of massive winter wheat, oilseed rape, and green onion cultivation. The first sector, mostly of winter wheat, in the southern part of Xinghua has an area of around 2.5 mi $\times$ 1.5 km. The northern portion of Xinghua was defined as a second zone with an area of roughly two and one km², largely consisting of oleaginous rape. The Third Green Zone was selected from the central part of Xinghua and occupies an area of around 2.1 km². Both unattended and supervised optimal SP selection methods were used in this thesis.

CHAPTER 2

LITERATURE SURVEY

2.1 Performance Analysis of Segmentation and Classification In HDR Satellite Imagery Using Neural Network IEEE 2018

Supriya A. Vaishnav; Sunil L. Tade

Satellite image processing is a topic that can be used for a variety of purposes, such as geological studies, soil analysis, agricultural applications, environmental impact analysis, natural hazard change detection, strategic planning to locate appropriate locations for urban development, and so on. The description of images is the most critical role in these applications. This thesis makes use of HDR satellite image data collection for pre-processing purposes. The dynamic range of the sky is normally 10⁶:1, while the dynamic range of the LDR is 10³:1. (Low Dynamic Range). As a result, in order to obtain an LDR image, this dynamic range must be compressed. To fix this problem, TMO (Tone Mapping Operator) is used, which provides excellent image visibility for excellent visualization.

Satellite images are extremely large, and standard displays are incapable of interpreting and comprehending the data contained in an image. To be interpreted and viewed, the whole image must be divided into small, big data components. To solve this problem, this segmentation technique must be used. There are several forms of fragmentation, such as Edge, Clustering, Watershed, and so on. In this analysis, we compared image segmentation based on clusters such as K-means, Mean transition, and SLIC by extracting various features such as processing time, mean, entropy, variance, and so on. In this article. This paper was linked to others. In this thesis, an HDR satellite image with a feed forward algorithm is categorized using an Artificial Neural Network (ANN) and a supervised analysis with accuracies of 99.53 percent.

2.2 Pixel classification of remote sensing satellite image using semi-supervised clustering IEEE 2019

Abhay Kumar Alok; SriparnaSaha; Asif Ekbal

Satellite pixels in homogeneous regions are difficult to come by since different regions occupy different types of soil. Few regions have large areas, and most have smaller areas (eg. bridges, roads). The number of clusters in satellite image segmentation has never been quantified before. We solved this problem in this paper by using semi-monitored clustering rules that combine unmonitored and supervised grading properties. Three cluster validity indices are simultaneously optimized by AMOSA using a modern multi-objective optimization approach based on the concept of simulated renewal. The first two cluster validity indices are the Sym-Index, which is based on a symmetry interval, and the Euclidean I-Index, which is based on unintended properties. Finally, the Minkowski Index is a cluster validity index that focuses on supervised expertise. Initially, the fuzzy C-mean clustering technique is used to track data. The highest membership values of the data points for different clusters are then used to pick 10% of data points with their class marks at random. The effectiveness of this suggested semi-monitored clustering strategy is demonstrated on a dataset of Indian satellite images.

2.3 Research on crop identification method based on two-phase classification using remote sensing in large scale, IEEE 2020

Qiong An; WanlinGao

This research takes Jilin Province of China as experimental field, gathers data on the ground survey, and assumes that the large scale and classification precision of the above system will satisfy output requirements. This study aims at improving the accuracy of identification and classification, and reduces sampling and extrapolation errors. The average precision attained is 96 percent, Quickbird reveals.

2.4 Advances in research on crop identification using SAR, IEEE 2019,

Di Wang; Qingbo Zhou

As a result, the accuracy and speed at which crop area surveillance is performed has a negative effect. As a new high-tech technology with a wide coverage of all-weather, all-time, and high resolution, synthetic transparency radar (SAR) was widely used in the field of agriculture monitoring and thus represents a great complement and support to crop identification in the area of data and technology. Remote sensing of crop information, growth conditions, and yield of SAR has been a significant field of agriculture in order to upgrade and enhance the function and performance index of radar sensors. This article extensively summarized the progress of studies and applications on crop discrimination by SAR, focusing on one central point: the development of radar technology over the last 20 years.

2.5 Crop-Identification Using Sentinel-1 and Sentinel-2 Data for Indian Region, IEEE 2018

Jitendra Singh; Umamaheswari Devi;

Due to the immense economic impact of farm crops, real-time monitoring is a significant activity. Early crop identification will aid in the development of better agricultural policies and management strategies. In this background, the aim of this paper is to assess the ability of Sentinel-1 Synthesis Apertures Radar (SAR) and Sentinel-2 optical images for crop identification in the Indian region. A multi-class random forest classification algorithm is used to cover the functionalities obtained from the above satellite data sets. Initial experimental evidence shows that Sentinel-1 SAR data has the potential to attain high classification precision (85 percent).

2.6 Research on Feature Selection Method Oriented to Crop Identification Using Remote Sensing Image Classification, IEEE 2019

Qiong An; WanlinGao

In this article, a two layer adaptive and multi-class JM distance model (AFSM) will be investigated. In order to increase the precision in the classification, the feature is handled correctly during the operation of crop identification using Remote Sensing (RS) image classification. First of all, with the MODIS data as examples, statistical methods and dynamic modifications are used to study derived spectral characteristics of temporal index series like NDVI, EVI, MSAVI, and NDWI. Secondly, rice is used for experimental purposes and the principle of multi-target operational analysis planning is applied.

2.7 Crop classification using feature extraction from satellite imagery, IEEE 2018

AsmaAkhtar; Muhammad Nazir;

Meat, medicine and industry are a significant source for plant life. But recognizing species of crops on Earth is a necessary and challenging challenge. It is therefore relevant to develop a suitable crop recognition method. With rapidly advancing the frontier of space science, remote sensing offers extremely convenient resources for agricultural production. We are proposing a new way of classifying crops from satellite imaging in this article. First of all, we put together a database of various crops and then extract from each crop the discrete Cosine Transformation (DCT) and Discrete Wavelet Transformation (DWT) characteristics and then classify them according to different classifiers.

CHAPTER 3

Aim and Scope of the present investigation

The classification and extraction of cover types from satellite/airial imagery has applications in a variety of fields, including defense, geography, agriculture, and surveillance for natural disaster damage, among others. However, satellite imagery analysis, especially in the case of MSIs, can be a difficult task. Typical machine learning approaches allow for the selection of an image in advance and the use of a classifier to detect the different cover types in the image. Detecting good characteristics/attributes, on the other hand, can be difficult in any classification issue. Deep Neural Networks (DNNs) avoid the issue of preliminary functional filtering by combining function extraction and classification into a single system. CNNs are attractive since the functional set is passed to the network, which optimally chooses the most suitable classification tasks.

I created a Convolutional Neural Network for patch-based classification of various land cover classes, which used a 64x64x13 image and allowed for multiple class assignments. The CNN had 11 hidden layers for feature recovery, including 6 convolutional and 3 pooling layers. A fully different classification layer and a dropout layer for overfitting were added to the convolutional layers (more about dropout and other regulatory strategies can be read). To speed up training in the convolutional layers, I used the ReLU activation function (as the gradient of ReLU is easy and fast to compute during backpropagation). To scale the values to reflect the class chance, I used a sigmoid activation function on the fully connected output sheet (I also hot encoded the class labels). The output layer of my network has ten neurons, each of which reflects the probability of the input image being classified. Since I'd still run out of memory due to a large number of spectral bands, I had to keep the batch size small. I had to settle for a batch size of 50 photos in the end. The dataset was divided in half for review and assessment. With planning and confirmation losses of 0.007 and 0.06, I was able to obtain an accuracy of 99.7% and 98.4%, respectively.

Existing methods for solving the recognition problem usually rely on segmentation and

feature extraction. One of the major issues that many existing algorithms face is their inapplicability in other fields. Many image segmentation and classification methods are well-suited to one problem and one area with well-known seasonal imagery shifts. Image segmentation is irregular as a result of the above-mentioned advances in acquisition technologies and disproportionate resolution, and the data can be divided into fixed-dimensional regions. Using in-depth learning algorithms, such as a convolutional neural network, is one way to solve the algorithm generalization problem.

Scene characterization with outstanding UC Merced Land Use data set results was previously achieved using CNNs for high resolution Remote Sensing (HRRS). These works make use of object recognition translation training with a CNN that had previously been trained and finalized for a remote sensing program. Ishii et al. used the support vector machine (SVM) to compare Landsat 8 images and discovered a CNN that outperforms FSM. For a boost of the random convolutional network, Zhang and Zhang suggested the scenario classification scheme (GBRCN). The authors claim that they outperform current state-of-the-art algorithms on UC Merced and Sydney (at 1.0 m spatial resolution) data sets, but they do not yet know how they are applied (as of 27 November 2015). Though CNNs are commonly regarded as a popular and promising approach to object classification, the segmentation issue can have many solutions, making it difficult to pinpoint the exact architecture of CNN.

CHAPTER 4

Algorithms Used

4.1 Satellite image filtering and enhancement using 2D Double density wavelet transform (2D DDWT)

Image enhancement are the result of satellites improving image quality without understanding what caused the degradation. If the cause of the degradation is understood, the picture restoration procedure described in Chapter 3 can be used. Both approaches are iconic, in the sense that they use images as input and output. To improve images, various simple and heuristic methods are used. Image restoration removes or reduces image degradations that have been registered. Many image processing systems may benefit from geometrical transformations. Image restoration, for example, where the decay process is often modeled as a space invariant, or measuring device calibration or correction to minimize the relative motion of the target and the sensor are both examples. A established geometric distortion should be omitted in both cases, as seen in the diagram.

Geometric rectification and the geometrical records of the hybrid mathematical model are discussed. The geometric rectification imaging must be modified in order to enhance the accuracy of illumination. Image enhancement techniques for remote sensing data are typically used to alter the appearance of an image so that it can be interpreted by humans.

The main focus of enhancement methods follows these procedures in to image segmentation, clustering and geometric transformations. In order to account for the acquisition scheme's flaws, several preliminary gray level adaptations, in addition to geometrical transformations, could be proposed. This is possible pixel by pixel as a product of a consistently light image calibration. Space-invariant gray value variations are often used to stretch contrast, compress coverage, and so on. The relative frequency is the critical distribution of each grey value, represented by the gray

histogram. Image enhancement techniques have reawakened significant interest in recent years, despite the fact that they are typically not used for automated testing techniques. Applications such as artificial worlds or battlefield simulations necessitate complex enhancements in order to create 'actual life' environments or process images in near real time. the major focus of these procedures is to enhance imagery data in order to display effectively or record the data for subsequent visual interpretations.

The parts of the image to be processed are calculated using a moving frame that encodes the local geometry (directions of gradients and level lines). Then, using our methodology, we de-noise the image fragments in the moving shutter, preserving their regional geometry and allowing them to be more directly affected by image processing. Though numerically impressive and theoretical limits are approaching, radical noise solutions are subject to measurable artifacts. Even when they see false photos, they are less accepting of medical or natural images. They provide appropriate results. At constant time, current strategies are getting a lot of complex, creating analysis, and implementation troublesome. The image de-noising algorithm is used as an easy physical method that increasingly reduces noise by settled hardening. The denoisome operations are carried out in order to protect the image accuracy. The technique for improving images requires restricted directional properties and sensitivity to change.

Dual Tree Wavelet Transformations were added to overcome these limitations. Moreover, as it is well-known that excessive transformations give greater balance between complexity and efficiency, double density wavelets are one of his examples. By doubling density wavelets to produce advanced double tree for the removal of Gussian noise the algorithm is a denoising technique. It limits the large coefficients on the basis of the NeighShrinkSure threshold and has been used for further flattening of median filter. The Double Density Wavelet Transform is used to perform different task of image processing, specifically, a dual-tree complex wavelet transform layer is concatenated to the standard pooling method in a very Convolution Neural Network (CNN). By using wavelet transform decomposition, the image becomes scalable in the spatial direction, permitting correct recognition of textures on the image.

The wavelet transform decomposes the image into variety of wave sub-bands, and reduces good knowledge by filtering out high-frequency sub-bands. Both the Kingsbury dual-tree and therefore the resulting Selesnick double-density dual-tree wavelet transform approximate an analytic performance. The classification of the part dependency across scales is basically undiscovered except. Here is a tendency to characterize the sub-band dependency of the orientation of part gradients by applying the Morel-Helmholtz principle to quantity histograms to find significant modes to improve the quality of the image. In contrast to other current techniques, neither image modeling nor noise statistics are essential for an image restoration approach. The variance of the detailed wavelet coefficients is used to determine whether these coefficients are to be smooth or preserved. The method uses wavelength transforming property to produce 3 detailed sub-images, each with unique information with bonded directional features. This allows the ability to blend coefficients from entirely separate detailed sub-images to direct filtering. The algorithm uses the hypothesis to see whether the distribution supports the choice if the image associated or the noise is the reason for detailed wavelet coefficients. Centered on the double-density wavelet transformation, an effective and precise approach to removal of speculative noise from frames by threshold evaluation strategies.

The utility of the proposed depeckling algorithm is greatly improved by combining two completely different threshold estimation technologies at completely different stages of DDWT decomposition. The threshold estimate is determined using VisuShrink and standard Shrink rules. During this process, the image is broken down into 9 DDWT substrates. Each of the informative subbands can be used to calculate the threshold values for VisuShrink to decomposition of DDWT 1st level and typical Shrink at high level. Noise is then eliminated using soft threshold technology. The reverse rework is applied later in order to obtain a noisy picture. On the fifth rank, the complicated twin tree twin tree, real double tree density, and complicated double tree density twin tree investigate the method's performance. After updating DDWT's basic theory and studying the frequency linkages between clouds and ground subjects in remote sensing

images, a brand new formula for excluding clouds from a remote sensing image was projected.

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The formula grouped the cloud polluted picture into low-level sub-bands, high-level sub-bands and low-frequency sub-bands by DTCWT. The formula The low-level HF-subband was filtered by Laplacian filtering to strengthen the low-level object data. The opposite 2 kinds have been processed by the Cloud Layer constant weight approach to get rid of the cloud (CLCW). The Laplacian has shown its contribution to the adaptive improvement of ground object data. CLCW will erase clouds when protecting the bottom object data outside of the inclemency. Researchers use either Fourier rework (FR) or Wavelet Transformation to execute in transform domain (WT).

The transforming wavelet works well with noise reduction applications in special discrete wavelet transformation. They suffer from low selectivity, shifting sensitivity disadvantage and a lack of knowledge for the components. The DWT is based on 2 scaling performance and 4 different wavelets, which are predicted double densities. In image denoision applications, this technique avoids the DWT's demerits and performs superior to ancient linear processing (for example, viennese filters), transformation of a stationary wavelet (SWT), DWT, DWT dual density and other applications.

In comparison to the two dynamic wavelett transformations and global threshold technical, the excellent results in terms of PSNR, MSE and Histogram of the predicted device. The distinct wave remodel double density DWT or double density double tree (DDDTDWT). The noise increases with the desired image information in the improvement. To restate this increased noise analysis, 2 types of threshold techniques, such as static and adaptive, have been developed. A random noise model is considered when illustrious noise examples from the input image are taken from the input instead of the unknown noise in the static threshold, as in the adaptive threshold. The combination of the threshold techniques to accepted noise thresholds in order to improve noise reduction and PSNR values would lead to a hyride threshold technique. The

DDTDWT method is used for this study and has much asymmetry than DTCWT and the soft threshold and shrinkage to reverse the noise.

Wang –Q Lim *et.al* has presented efficient multi-scale directional representation that is called discrete shearlet transform (DST). Discrete framework built the implementation of the transform based on multi-resolution analysis (MRA). The DST outperforms the discrete wavelet transform (DWT) in image approximation while the computational cost is comparable to the DWT. The DST compares favorably with other existing transforms in image noising. Yuriy.Vet.*al* has presented the feature-enhanced radar/ fractional synthetic aperture radar computational imaging exploit new multistage iterative SR technique. The sparsity of the desired image representations in some appropriately chosen over complete dictionaries are suggested by coherent remote sensing imagery. Each nested refined super-resolution (SR) frame have multistage resolution enhancement (RE) it perform consequently via iterative reconstruction of up-scaled radar images followed by the discrete wavelet transform. Miroslav Vranik and victor sucic*et.al* have presented the novel adaptive wavelet filter bank structure to exploit lifting scheme based on quincunx sampling. The desirable numbers of primal and dual vanishing moments are retained from filter bank. Filter bank provide adaptation in predict stage based on the intersection of confidence intervals rule. The image de-noising results of both synthetic and real world images are showed.

Zhen James Xiang and Peter J. Ramadge*et.al* have presented theoretical basis for optimal dyadic wavelet decomposition structure using new regularize, it preserves edges . The composition of the dyadic tree, the complicated action of the waves, the morphological wavelets and the regularization of smoothness in Besov space are connected into a consistent system for regularization of images. This normal and ideal dyadic wave decomposition structure is a regular image de-noising algorithm. M. Dirk Robinson and Cynthia A. Toth *et.al* have presented high resolution and high quality image with super-resolution (SR) based on combined Fourier wavelet de-convolution and de-noising algorithm. Restoration and de-noising of the fused images are the key process of SR. Computationally efficient method leverages the efficiency of the fast Fourier transform, it minimize the complexity these demonstrate the effectiveness of this

algorithm for regular imagery . Yaniv H. Mehnert *et.al* have presented algorithm for de-noising dynamic contrast enhanced (DCE) MR images named as dynamic nonlocal means (DNLM), it relative to seven other de-noising methods.

Quantitative evaluations using both simulated and real data .The simulated data from the results show the smallest MSE between de-noised image and its corresponding original noiseless version based DNLM algorithm, it demonstrate the DNLM algorithm is effective and better than other algorithms. Alexander Wong and Akshaya K. Mishra *et.al* have presented de-noising MRI data using Quasi-Monte Carlo estimation approach (QMCE). General Bayesian least square estimation problem formulated from the estimation of noise- free signal. QMCE used MR data volumes and synthetic noise for noise reduction. QMCE is effective compared to other methods it provides effective noise suppression. Ivan W. Selesnick *et.al* has presented vanishing moments in dyadic wavelet frames with two generators to cover the time frequency plane. The performance of sampling in time and frequency are higher.

The spectrum of the first wavelet is concentrated halfway and the second wavelet is translated by half integers it provides an expansive wavelet transform that is approximately shift invariant and has intermediate scales. Bogdan Dumitrescu and Ali Bahrami Rad *et.al* have presented the designing technique for dual-tree double-density discrete wavelet transform (DWT). Hilbert transform of a transfer function involving a half delay gives approximation of high pass filter. The nonlinear optimization is refined the obtained filters .It shows the perfect reconstruction constraints and resulting pair of wavelets. Shang Zhaowei and Wang Jie *et.al* [20] have presented retrieval method for texture image from the extension of The refined Histogram to model the magnitude of the two-density dual wavelet complex coefficients, the extension of RH provides analysis of non uniform quantize and RH. It combines effective RH and the shift invariant DD-DT CWT and gives superior performance.

42 Image degradation noise sources

A image is distorted by a particular kind of noise. Also noise is divided into two categories: substitution and additive noise. Impulse noise is another name for replacement noise. These sounds like salt and pepper noises, impulse, and so on. Gaussian additive white noise is used as additional noise. Noise in optical images appears to have a constant influence across the entire bandwidth and is vulnerable to Gaussian distribution. This kind of noise is known as white Gaussian additive noise.

43 Gaussian Noise

Gaussian noise is a mathematical ring with a conventional distribution probability function (pdf) that represents a part of the "read noise" of an image variable with a constant amplitude in dark image areas. Gaussian noise is also known as electrical noise. The noise values of Gaussian noise are distributed Gaussian. White Gaussian noise is a form of statistical noise in which the values are continuously scattered. White gaussian noise additives are often created using Gaussian noise. Because a Gaussian amplitude distribution noise indicates the interaction between time noise and spectral noise density, Gaussian noise is often described. Noise in Gaussian is the same as dissonance in white math, which describes the interaction of noise.

44 Salt and Pepper Noise

The picture noise from salt and pepper will include dark pixels and light pixels in bright areas in dark areas. Noise caused by Salt & Pepper was also caused by dead pixels, converter analog, bit errors, etc. It is all about white and black pixels. It reflects itself. Noise models Salt and Pepper, only 2 values "a" and "b" are available The chances of of of them being achieved are less than negligible. 1) 1. 1. 1. The amplitude for pepper noise is normally close to zero for 8 bits/pixel image and about 255 for salt noise. Noise from salt and pepper could normally be a common noise in photographs. The noise itself reflects white and black pixels as either way in the picture parameters.

45 Speckle Noise

Blue noise is a form of granular noise that occurs naturally in images and degrades image quality. As Satellite Aperture Radar (SAR) images are not a legacy of the active radar, speckle noise tends to break the image. Because of random signal fluctuations in typical radar objects, which aren't significant where noise is present in the individual picture processing component, The average gray amount in a region is raised by speckle noise. Noise from speckles is a significant issue that creates issues with image recognition in SAR videos. The system is primarily responsible for backscattered signals from numerous distributed targets. The standard speckle noise causes the random fluctuation within the signal of an object that is not larger than one image preceding component. A region's mean gray quantity will be raised. Underneath the image of the oceanwaves, gravity - capillary ripples, speckle noise is caused by elementary dispersal signals.

46 Proposed Image restoration algorithm using 2D Double Density Wavelet Transform (2D DDWT) based 2D Adaptive Bilateral Filter (2D ABF)

The DWT is associated with improved DWT with important extra properties: (1) it is based on a single scaling operation and two distinct waves, built to be compensated by half from each other, (2) the DwT with double density is almost invariant by an aspect of 2, and (3) in the 2D image, this remodel outperforms the DWT de-noise quality; however, since not all wavelets are directed, there is room for improvement. While the DWT dual density employs additional wavelets, some lack a superior spatial orientation, making it difficult to isolate these directions. The current problem can be solved by using the 2D Double Density Wavelet Transform, which incorporates the properties of the double density DWT and, hence, the double tree DWT.

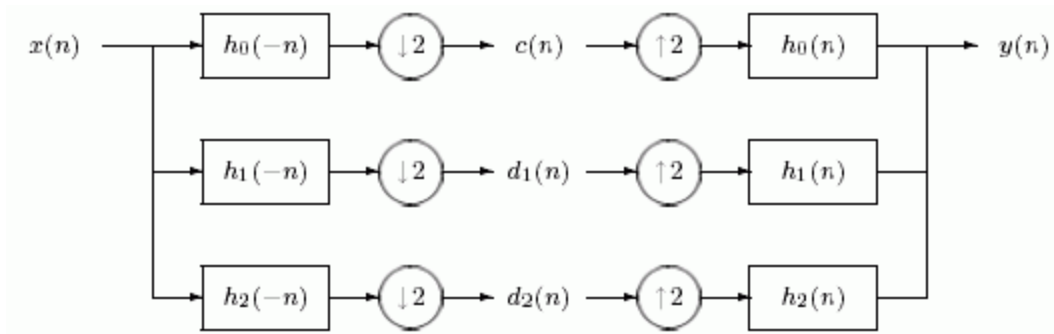


Figure 4.1: 2D Double Density Wavelet Transform (2D DDWT) decomposition

The 2D transform wavelet double density (2D DDWT) with sufficient filter selection is shown by Figure 1. The filter bank of the study consists of three filters of analyzes, one low-pass filter with $h_0(-n)$ and two separate high-pass filters with $h_1(-n)$ and $h_2(-n)$. Since the $x(n)$ signal passes by the device,

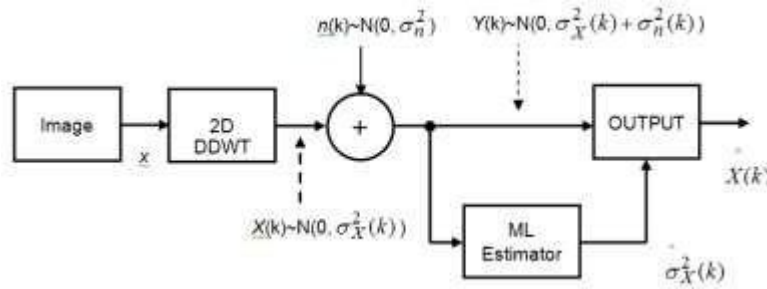


Figure 4.2: Image de-noising using 2D DDWT

The image de-noising 2D DDWT is illustrated in figure 2. The noisy is image is formulated as shown in the figure. The 'pure' image, x , is decomposed by applying 2D DDWT gives the 2D wavelet coefficients $X(k)$. These wavelet coefficients, that may be considered as random variables with the noise variance $\sigma_X^2(k)$ those are degraded by additive Gaussian noise, $n(k)$, to prepare the wavelet coefficients of the degraded image $Y(k)$. Here, W and W^{-1} are the 2D DDWT and inverse transformation respectively. The significance between image and transformation wavelet coefficients is,

$$X = a^* W x \quad \text{and} \quad x = a^* W^{-1} X \quad (1)$$

The pure image coefficients, is the estimated value from the calculated coefficients, Y , the noise variance, σ_n^2 and 2D image coefficients variance, $\sigma_X^2(k)$ are calculated using above equation . The robust estimator of the sub-band diagonal matrix coefficients (i.e. HH₁) calculates the image noise variance. The image coefficient variance, $\sigma_X^2(k)$, is estimated using the estimated noisy information in a small area that is obtained as variable size blocks on the scales. Finally, the estimator gives an estimation on the 'pure' coefficients, $X(k)$, the filtered image is given as,

$$\hat{x} = W^{-1} \hat{X}$$

Edge preservation Smoothing is an important technique that is applied to smooth away the textures while preserved in sharp edges. Edge preservation smoothing techniques that decomposes the image to be filtered supported. A base layer is created by consistent region with sharp edges and another layer is detail layer which might be either noise. For example, random patterns with zero mean or texture. In edge preservation smoothing techniques are additional classified in to varieties one. It produces good quality with high process price based on 2D ABF that are extension in gradient domain. The 2D ABF may be a spatial average, smoothing edge non-linear filter; the technique of de-noising of images is seen to be accurate. The implementation of the 2D ABF is a big problem, since the selection of filter parameters has a significant impact on the performance.

The suggested scheme contains two key inputs. The primary contribution in image denoise applications is empirically based on the optimal 2D ABF parameter. Secondly, the expansion of the bilateral filter: bilateral multi-resolution filter, in which 2D ABF is added to a 2D DDWT filter bank for approximating (low frequency) symbol subbands. In conjunction with the moving wavelet threshold, the multi-resolution 2D ABF provides a fine image de-noise frame which is very useful in removing sound in actual images. The design of 2D DDWT and 2D ABF for the de-noising of images is seen in illustration 3.

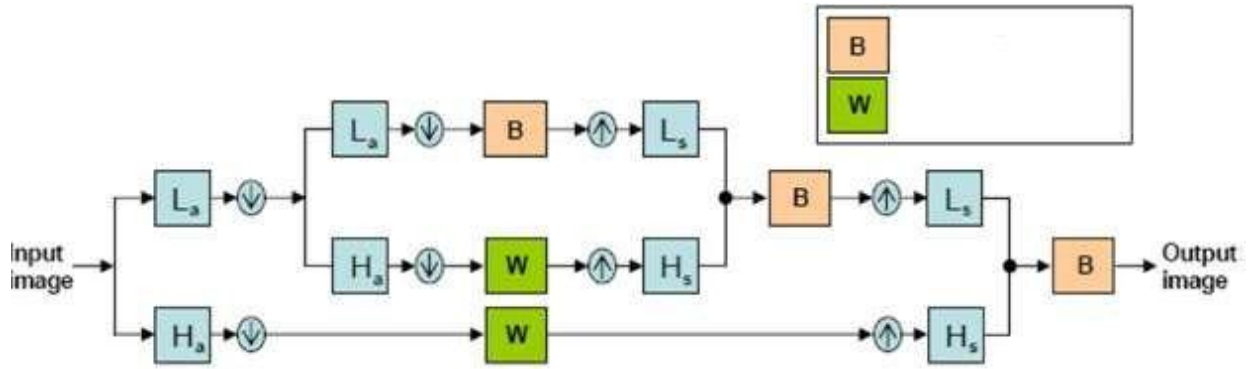


Figure 4.3: Architecture of proposed filtering technique using 2D DDWT

The adaptive mean adaptation algorithm is designed to boost the filter image. AMA stretches and flattens the dynamic contrast and brightness difference. As a result, image accuracy is improved. The luminosity of the corresponding input signal, on the other hand, may be greatly altered. The transformation is made possible by the subsequent interactions. A high frequency filter transforms the mean into the optimal histogram, and the histogram is generalized to match the distribution. We believe that a high-frequency filter misprocessed the target histogram for histogram specification.

The histogram technique converts the histogram of the input image to the given mean value. After that, the protocol converts the input image to a chosen mean. In the histogram specification, the histogram specified is extremely critical. We have a tendency to get the best impression that matches the histogram. To obtain the best histogram, a high frequency filter is used. Stretching the histogram is a popular technique for enhancing photographs. The distribution of black and white histograms is used in the medium. Darker and lighter pixels with darker elements are made. The suggested strategy splits each substratum's histogram into two medium-strength histograms and expands the left field histogram.

4.7 Satellite crop image classification using Deep Neural Network (DNN)

A neural network can be likened to a computer playing chess. Depending on the actions and moves, there are formulas that can be used to evaluate tactics. The programmer specifies how each figure is entered into the machine's memory, determines the size of the chess board, and proposes a vast number of chess tactics. For instance, the robot will learn from both you and other people at the same time, transforming into a deep neural network. Playing with different teams will become unstoppable after a while.

Since the neural network is not a novel system, a profound neural network is much more difficult. It will be able to identify voice commands, recognize sound and graphics, verify experts, and perform a variety of other tasks that include prediction, creative thinking, and research. And the human brain is capable of doing so. A deep network can approach a problem in a globally more complicated way, drawing conclusions or predictions based on the information given and the desired result (a name, action, number, or solution). A deep neural network will solve a problem if it has a consistent input of data and solution algorithms, and it will not solve a problem if it does not have vast amounts of marked data.

The neural network must constantly train in order to solve tasks or to use alternative ways to produce a better result. When new information is added to the scheme, it learns how to act appropriately in new situations.

When tasks are solved, learning gets deeper. Deep neural network is the type of machine learning where the algorithm uses a large number of node layers to obtain high-level knowledge functions. It means the data is transformed into an abstract and artistic element.

To better understand the result of deeper learning, consider a picture of a regular person. You will still recognise this image, voice, and body as human and discern it from other species, even though you have never seen it before. This is an example of how a deep neural network works. Creative and analytical information elements are analyzed and grouped in order to ensure correct subject recognition. These components are not

directly introduced into the system; instead, the ML system must modify and derive them.

There are several types of neural networks, and the differences can be found in the concepts of operation, scheme, and application areas. CNNs are often used in image recognition but not in audio recognition. It's just for pictures, so all pixels don't have to be tested individually. CNN examines an image block by block, shifting pixel by pixel from the upper left angle to a satisfactory conclusion. The results of each test are then sent to a convolutional layer, where certain data components have connections and others do not. Based on these numbers, the computer will derive the outcomes of the checks and assume what is in the picture.

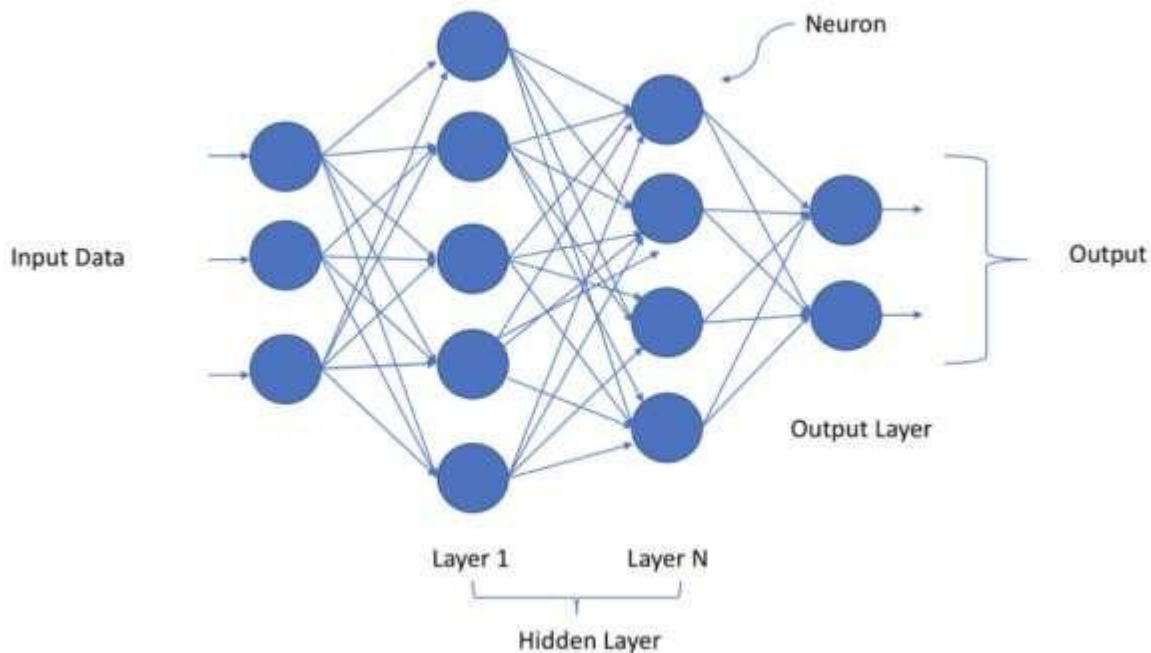


Figure 4.4: Deep Neural Network architecture

As seen in the diagram above, neurons in the first layer (not hidden) absorb the input data, which is then passed on to neurons in the next layer, and finally to the final output. The outcome could be either a yes or no prediction (represented in probability). Each

layer contains one or more neurons, each of which measures a small activation mechanism, i.e. the activation mechanism imitates the signal to transfer to the next neurons involved. If the incoming neurons obtain a value greater than a threshold, the output is otherwise ignored. For each successive sheet, there will be a corresponding weight of two neurons. The weight decides the effect of the input on the output of the next neuron and, ultimately, on the overall end output. All of the initial weights are altered in a neural network, but these weights are changed iteratively during model testing so that the correct performance is forecasted. When we decompose the network, we can define multiple logical component blocks, such as neuron, sheet, weight, data, result, activation function, and, finally, a learning process (optimizing mechanism). This will assist the neural network in gradually upgrading its weights to a more acceptable weight, allowing the outcomes to be estimated correctly.

Consider how a human brain can identify people using an abstract understanding. When you meet a human for the second time, you will recognize him. How do you go about it? The people's general configuration is similar: two eyes, two ears, a nose, a mouth, and so on. Both people have the same form, but we can clearly tell them apart, right?

The core of the brain learning process is simple. Instead of examining the morphology of the face to differentiate entities, the deviation from the generic facet, that is, how his eyes differ from the reference eye, can then be quantified as an electrical signal of a certain frequency. Similarly, it learns deviations from each part of the face from a reference point, incorporates these changes in new proportions, and finally produces an output. Much of this happens in a split second, and neither of us is aware of what our subconscious mind is doing.

As seen above, the neural network often tries to mathematically mimic the same procedure. In the first layer, neurons ingest the signal, and each neuron calculates the activation mechanism. It sends an output to the next neuron based on a basic rule, similar to how the human brain handled deviations. The input dimension becomes more significant as the neuron production becomes greater. These dimensions are then

combined into the following sheet, which we may or may not be able to understand. The computer, on the other hand, intuitively recognizes this. As the approach is repeated several times, it produces a complex network of several connections.

Now that you understand the essence of the neural network, let us clarify how learning occurs. If we presented the input data for the given form, the output will be a projection (with a matrix multiplication series), which may be right or wrong. If we provide feedback to the network to improve it with means to help forecast them, the system learns by updating the weight of the links based on their results. To accomplish the input process and determine the next step to make improvements, we use a beautiful mathematical algorithm called 'backpropagation.' The system is activated multiple times as more data is collected, allowing the network to correctly adjust weights and build a structure that can forecast output using weights and links based on rules it has generated for itself.

Deep neural networks were developed from the use of several more hidden layers and became a 'deep' network with more complex models. The success stories of deep learning have only appeared in recent years as the network's education process is computer-intensive and requires vast quantities of data. Finally, the experiments only came to light as the availability and price of the calculation and data was increased.

CHAPTER 5

RESULTS AND DISCUSSION

Satellite images – Modis Database

Modis database are Indian database

It is spectral images (R, G, B Layers Images)

Band – RGB Band

Web site URL: <https://ladsweb.modaps.eosdis.nasa.gov/alerts-and-issues/?id=53912>

Image Width, Height: 1024 x 1024

Noises: Speckle noise, salt and pepper noise, Gaussian noise

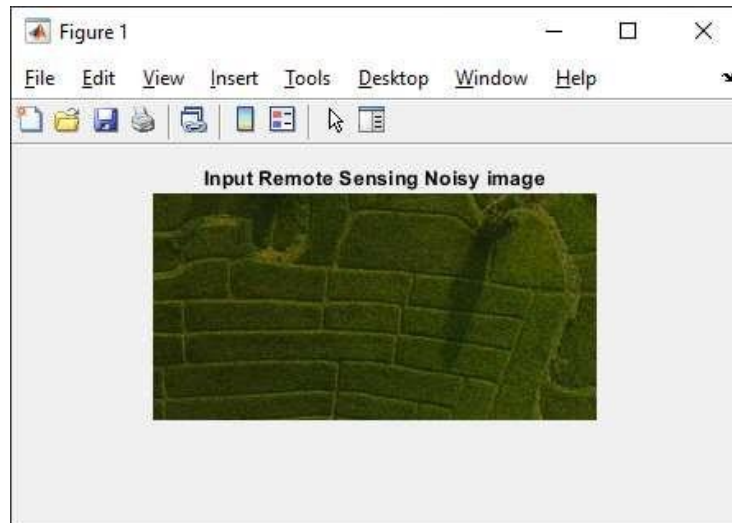


Figure 5.1 :Input Remote Sensing Noisy Image

Here the required image is acquired

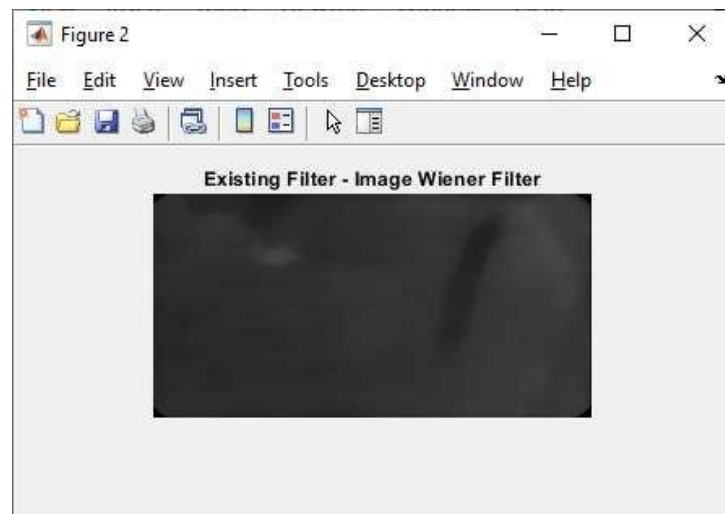


Figure 5.2 :Existing Filter- Image Wiener Filter

Here the image shown is the usage of the existing Wiener Filter

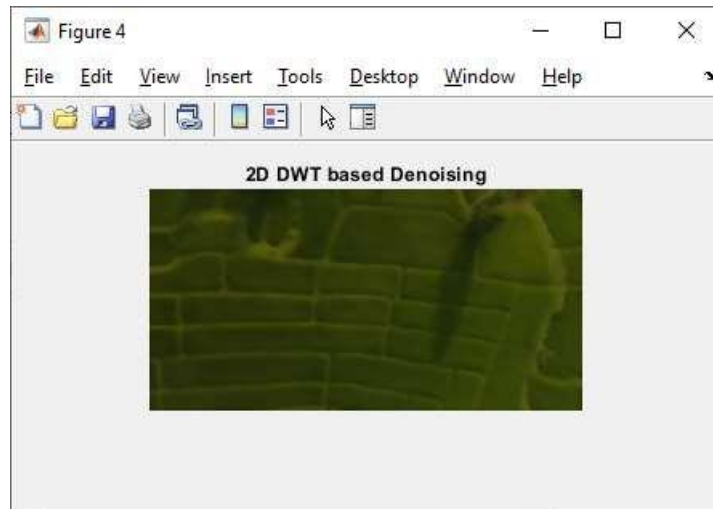


Figure 5.3:-2D DWT Based Denoising

Here the above image shows partially denoised image using 2D DWT

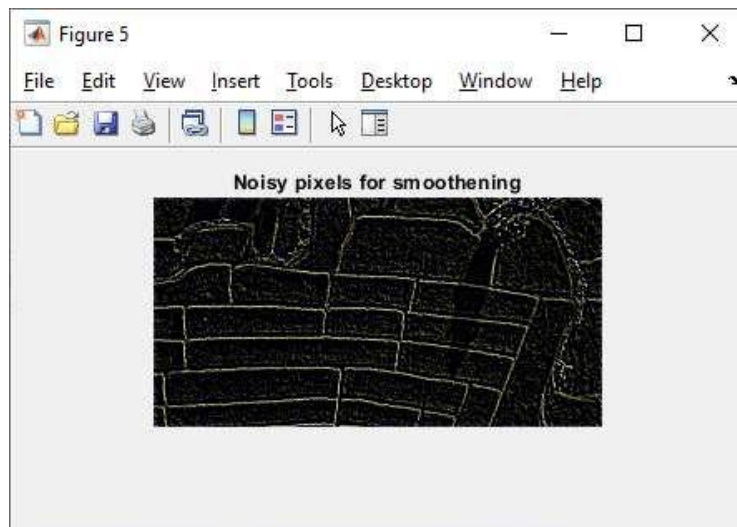


Figure 5.4:-Noisy Pixel for Smoothing

The above Image shows the noise which is present in the image



Figure 5.5:-2D DDWT Based Denoising and Enhancement

In this above image the proposed 2D DDWT based denoising is done and the image gets noise removed

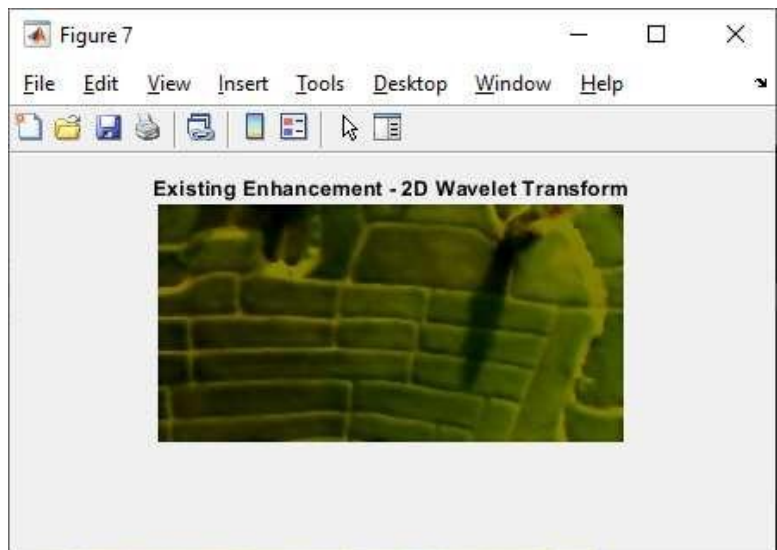


Figure 5.6:-Existing 2D Wavelet Transform

The above image is Existing Enhancement which can remove noise but not as much as proposed system

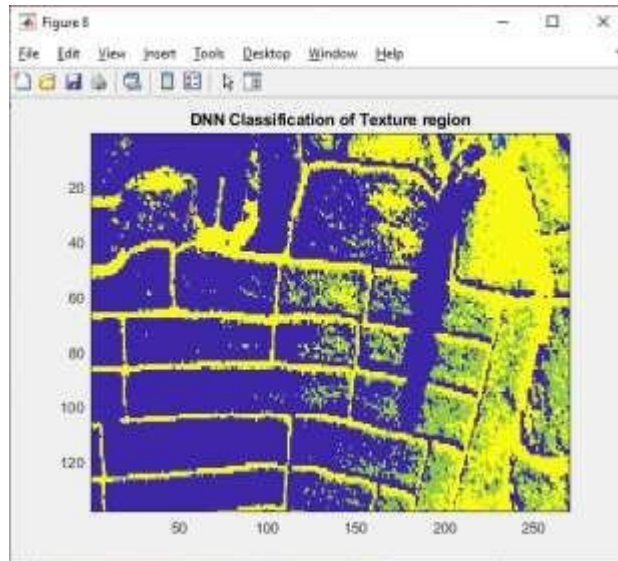


Figure 5.7:-DNN Classification of Texture Region

Here the classification of Texture Region is done using DNN Classification which helps the DNN to understand what type of crop it is

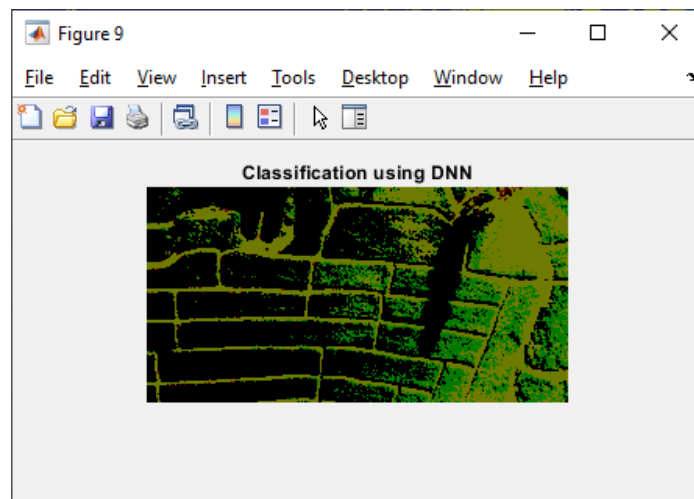


Figure 5.8:-Classification using DNN

In the above Image the classified Texture Region image gets read and trained to say the final result

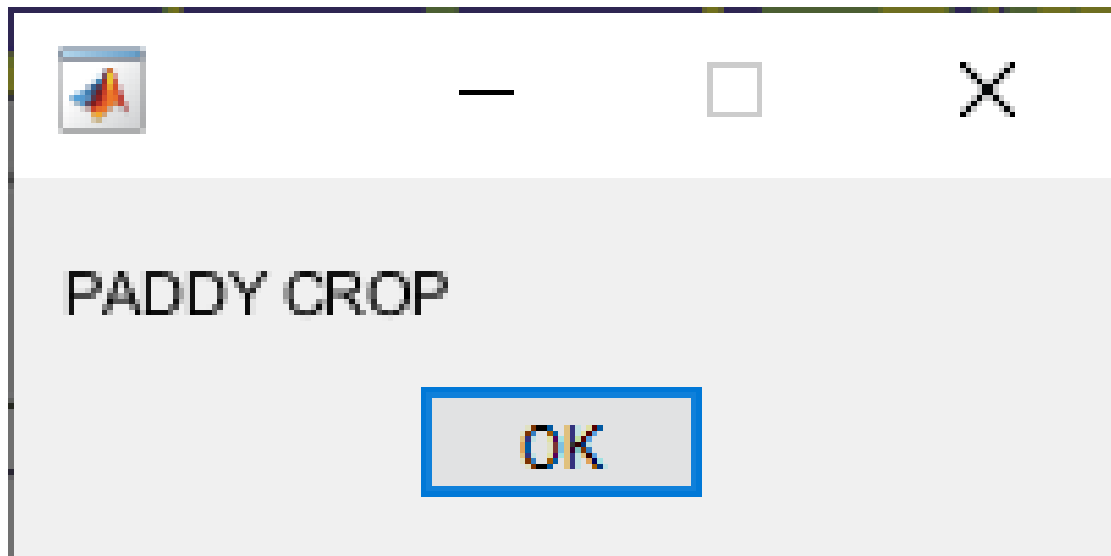


Figure 5.9:-Result

The above image shows type of classified crop

The usage of the 2D DDWT and DNN is the best way to get an acquired image out of noise and we train DNN using multiple images and we can detect multiple crops which is very useful. The proposed system has Accuracy rate of 96.3% in classification.

Table 5.1:- Comparison of 2D Wiener Filter – Existing and 2D Adaptive Wiener Filter – Existing to the 2D DWT

Images	Types of Filter	PSNR in dB	MSE
Paddy image 1	2D Wiener Filter - Existing	23.3989	103.3989
Paddy image 1	2D Adaptive Wiener Filter - Existing	23.3989	30.3989
Paddy image 1	2D Discrete Wavelet Transform	52.2989	0.0398

The DWT is associated with improved DWT with important extra properties it is based on a single scaling operation and two distinct waves, built to be compensated by half from each other, the DWT with double density is almost invariant by an aspect of 2, and in the 2D image, this remodel outperforms the DWT de-noise quality; however, since not all wavelets are directed

Table 5.2:- Comparison of accuracy, Sensitivity and Specificity of Existing Neural Network and DNN

Types of classification	Accuracy in %	Sensitivity in %	Specificity in %
Back Propagation Neural Network	89.3976	86.3878	87.3989
Radial Bias Neural Network	92.3989	91.3989	89.3878
DNN	96.3989	96.3976	95.3983

BPNN-The actual performance of backpropagation on a specific problem is dependent on the input data Backpropagation can be quite sensitive to noisy data you need to use the matrix-based approach for backpropagation instead of mini-batch.

RBNN-training in RBNN is faster than in Multi-layer Perceptron (MLP) takes many interactions in MLP.

DNN-storing information on the entire network Artificial neural networks learn events and make decisions by commenting on similar events. Artificial neural networks have numerical strength that can perform more than one job at the same time It is more accurate

CHAPTER 6

SUMMARY AND CONCLUSION

SUMMARY:

We saw how a CNN can be used for pixel-level classification and then segmentation enhancement. A large area was labeled entirely in different groups at the pixel level: sugarcane, paddy field, tree, and so on. The choices were studied and used to classify the single layer CNN's architecture parameters. A context size of about 25 pixels, filter measurements, and pooling dimensions that resulted in less than 600 output units, and a limited number of filters, 50, were found to be able to achieve a stable high classification precision while retaining a short training and testing time. The classification accuracy was somewhat better for contexts 35 and 45, but the findings were more inconsistent and took longer. Many CNNs were used in combination with different context areas based on this discovery to achieve accurate and correct classification results. A combination of four CNNs with different history durations generated the best classification accuracy.

CONCLUSION:

Future research will look at the use of a CNN for unsupervised pixel classification using unlabeled results. Another path for future research is to create a method that is particularly adept at dealing with shadows. Shadows are objects that are implicit in orthographic representations and cannot be reasoned about by a CNN. To change the classifications of segments with low estimation certainty, a top-down logic technique can be used to assume estimated locations for shadows and use this relationship knowledge.

References

- [1]. Benediktsson, J.A.; Chanussot, J.; Moon,W.M. Advances in very-high-resolution remote sensing. *IEEE Proc.*2013, 101, 566–569.
- [2]. Castelluccio, M.; Poggi, G.; Sansone, C.; Verdoliva, L. Land Use Classification in Remote Sensing Images by Convolutional Neural Networks; Available online: <http://arxiv.org/abs/1508.00092> (accessed on 12 April 2016).
- [3]. Couprie, C.; Farabet, C.; LeCun, Y.; L. Indoor Semantic Segmentation using depth information.on Learning Representation, Scottsdale, Arizona, 2–4 May 2013.
- [4]. Farabet, C.; Couprie, C.; Najman, L.; LeCun, Y. Learning hierarchical features for scene labeling. *IEEE Trans. Pattern Anal. Mach. Intell.* 2013, 35, 1915–1929.
- [5]. Glenn, N.; Mundt, J.; Weber, K.; Prather, T.; Lass, L.; Pettingill, J. Hyperspectral data processing for repeat detection of small infestations of leafy spurge. *Remote Sens. Environ.* 2005, 95, 399–412.
- [6]. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*; Curran Associates: North Miami Beach, FL, USA, 2012; pp. 1097–1105.
- [7]. Lai, K.; Bo, L.; Ren, X.; Fox, D. A large-scale hierarchical multi-view RGB-D object dataset. In *Proceedings of the IEEE International Conference on Robotics and Automation*, Shanghai, China, 9–13 May 2011;pp. 1817–1824.
- [8]. LeCun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. Gradient-based learning applied to document recognition. *IEEE Proc.* 1998, 86, 2278–2324.
- [9]. Netanyahu, N.; Le Moigne, J.; Masek, J. Georegistration of Landsat data via robust matching of multiresolution features. *IEEE Trans. Geosci. Remote Sens.* 2004, 42, 1586–1600.
- [10]. Peña-Barragán, J.M.; Ngugi, M.K.; Plant, R.E.; Six, J. Object-based crop identification using multiple vegetation indices, textural features and crop phenology. *Remote Sens. Environ.* 2011, 115, 1301–1316.
- [11]. Penatti, O.A.; Nogueira, K.; dos Santos, J.A. Do deep features generalize from everyday objects to remote.

- [12]. Pradhan, B.; Lee, S. Delineation of landslide hazard areas on Penang Island, Malaysia, by using frequency ratio, logistic regression, and artificial neural network models. *Environ. Earth Sci.* 2010, 60, 1037–1054.
- [13]. Quigley, M.; Batra, S.; Gould, S.; Klingbeil, E.; Le, Q.V.; Wellman, A.; Ng, A.Y. High-accuracy 3D sensing for mobile manipulation: improving object detection and door opening. In *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Kobe, Japan, 12–17 May 2009; pp. 2816–2822.
- [14]. Reed, B.; Brown, J.; Vanderzee, D.; Loveland, T.; Merchant, J.; Ohlen, D. Measuring phenological variability from satellite imagery. *J. Veg. Sci.* 1994, 5, 703–714.
- [15]. Running, S.; Nemani, R.; Heinsch, F.; Zhao, M.; Reeves, M.; Hashimoto, H. A continuous satellite-derived measure of global terrestrial primary production. *BioScience* 2004, 54, 547–560.
- [16]. Socher, R.; Huval, B.; Bath, B.; Manning, C.D.; Ng, A.Y. Convolutional-recursive deep learning for 3D object classification. In *Advances in Neural Information Processing Systems*; Curran Associates: North Miami Beach, FL, USA, 2012; pp. 665–673.
- [17]. Vaduva, C.; Gavati, I.; Datcu, M. Latent Dirichlet Allocation for spatial analysis of satellite images. *IEEE Trans. Geosci. Remote Sens.* 2013, 51, 2770–2786.
- [18]. Weng, Q.; Lu, D.; Schubring, J. Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. *Remote Sens. Environ.* 2004, 89, 467–483.
- [19]. Xia, G.S.; Yang, W.; Delon, J.; Gousseau, Y.; Sun, H.; Maître, H. Structural high-resolution satellite image indexing. In *Proceedings of the ISPRS TC VII Symposium-100 Years ISPRS*, Vienna, Austria, 5–7 July 2010; Volume 38, pp. 298–303.
- [20]. Yang, Y.; Newsam, S. Bag-of-visual-words and spatial extensions for land-use classification. In *Proceedings of the ACM International Symposium on Advances in Geographic Information Systems*, San Jose, CA, USA, 2–5 November 2010; pp. 270–279.
- [21]. Yang, Y.; Newsam, S. Comparing SIFT descriptors and gabor texture features for classification of remote sensed imagery. In *Proceedings of the International Conference on Image Processing (ICIP)*, Cairo, Egypt, 7–11 November 2008; pp. 1852–1855.

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