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A Review on Deep Learning Neural Network Datasets for Satellite Imagery

M.P. Vaishnnave[1], K. Suganya Devi[2], P. Srinivasan[3], G. Arut Perum Jothi[4]
[1]*Dept of CSE, University College of Engineering, Panruti*
[2]*Assistant Professor, Dept of CSE, University College of Engineering, Panruti*
[3]*Assistant Professor, Dept of Physics,University College of Engineering*
[4]*Dept of CSE,University College of Engineering*

Abstract: Satellite Imagery Scene classification has been receiving a remarkable attention as it plays a vital role in a wide range of applications. Also, there has been an massive growth in Deep learning in many fields such as computer vision and natural language processing. Compared to the machine learning framework, deep learning has a strong ability in learning and the use of data extraction. An huge growth in the amount of publicly available satellite imagery and overall satellites launched, which has imposed a challenging data problem of how to label or classify objects on satellite imagery. This problem can be solved by deep learning techniques. A significant efforts have been taken to develop a variety of datasets and also to present a number of approaches that use these datasets for scene classification from satellite imagery.

Keywords: Machine Learning, Deep learning models, satellite imagery datasets, convolutional nueral networks,Satellite Imagery scene classification

I. INTRODUCTION

Earth Observation (EO) is a process of gathering the information about planet Earth through remote sensing. The location, where we can collect the most data about our planet, is in space [1]. Earth Observation information has numerous utilizations like forecasting weather, urban growth studies, biodiversity, land-use change such as natural disasters, natural resources such as fresh water and agriculture and wildlife studies.[2]Sensors used in remote sensing are called so because they have the ability to gauge (sense) interactions between earth surface materials and electromagnetic energy. These sensors are broadly categorized as active and passive sensors. Passive sensors use existing energy sources (commonly, the sun), while active sensors produce their own energy[3]. Optical imaging from satellites/aircrafts is a form of passive remote sensing, where electromagnetic energy from the sun in the visible spectrum that is reflected on the earth is used to capture photographs. Earth observation data is gathered by a range of techniques, and can be roughly categorized as remote and proximal (sometimes referred to as in-situ) sensing[4]. Imaging is the visual representation of an object’s form.Spectral imaging is a division of spectroscopy in which a complete spectrum or some spectral data is gathered at every location on the image plane and is processed. The term Hyperspectral imaging comes under Spectral imaging. Hyperspectral imaging is the gathering and processing of information from across the electromagnetic spectrum. The spectral purpose is the main factor that differentiates hyperspectral imagery from multispectral imagery[5]. Hyperspectral imagery contains bands with narrow wavelengths while multispectral imagery contains bands with broad wavelengths. The advantage of using hyperspectral data over. Multispectral data is the ability to define surface features with a higher spectral resolution.Recent technological advances in microelectronics have also spiraled into the satellite manufacturing industry. The miniaturization of space grade components has resulted in the rise of small satellites, including a great number of remote sensing satellites[5]. With reduced launch and manufacturing costs, this has prompted a democratized access to space. In turn, satellite imaging (a subset of remote sensing) has experienced an increase in interest and demand over the most recent couple of years, with imagery so far available only to very few research groups becoming much more publicly available[6]. Adding to this, the rise of new markets has driven commercial satellite imaging away from mere pixel pushing to content providing - wherein the strength of the imagery lies in how insightful it is. Historically, manual analyses of satellite and aerial imagery was feasible primarily because the volume of images available was quite low - but that is not the case now. Relevant data extraction from images, thus becomes a problem with the high volume of data we deal with today. A major component of these problems is the annotation (or labeling), where in one identifies the structures and patterns visible in a satellite image. Machine learning techniques have supported to be strong candidates here, especially in the recent year. Machine learning, research stems from the idea that a computer can be given the ability to learn, as a human would do, without being clearly programmed[7]. Deep learning is a subgroup of machine learning,

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and refers to the application of a set of algorithms called neural networks, and their variants. In such techniques, one offers the network with a set of labeled examples which it learns, or trains on[8]. Labeling these examples is done in many ways. Machine learning feature extraction is done by manually and classification is done by machine as shown in fig2. However , in deep learning both the feature extraction and the classification are done by machine as given in fig1. So Deep Learning neural network is more efficient to identify the Satellite Imagery.

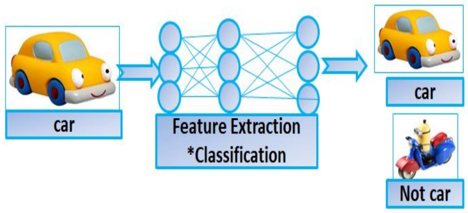

Fig1. Deep Learning neural networks

This paper is organized as follows: Section I and section II introduces the satellite Imagery and the Machine Learning model for the naïve users. Section III and Section IV discuss about the Convolutional Neural Network and Deep Learning. Section V provides a comprehensive review on various datasets available for sateliite imagery scene classification. A detailed review on various approaches and frameworks used for deep learning is discussed in section VI. Section VII lists some Literature gaps in Deep Learning for Satellite Imagery; Section VIII deals with state-of-art quantitative evaluation metrics for deep learning models for satellite imagery; Section IX discusses the concluding remarks.

II. MACHINE LEARNING

Artificial Intelligence can allow the computer to think. Computer is made much more intelligent by Artifical Intelligence. Machine learning is the subfield of Artifical Intelligence study. Various researchers think that without learning, intelligence cannot be developed[7]. There are many types of Machine Learning Techniques are Supervised, Unsupervised ,Semi-supervised, Reinforcement, Transduction and Learning to learn.

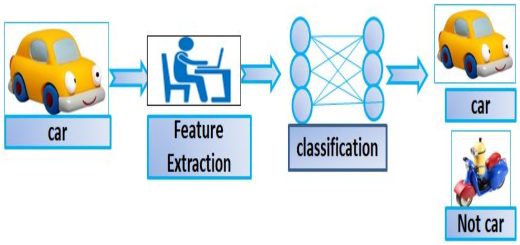

Fig2. Machine Learning.

1) *Supervised Learning:* All information is labeled and the algorithms learn to predict the output from the input information. Supervised learning problems can be additional grouped into regression and classification problems[9].
a) *Classification:* A grouping problem can used when the output variable is a category, such as “pink” or “black” or “car” and “no car”.
b) *Regression:* A regression problem is when the output variable is a real value, such as “rupees” or “coin”. Some popular examples of supervised machine learning algorithms are: Linear regression, random forest for classification and regression problems and Support Vector Machines for classification problems.
2) *Unsupervised learning:* All information is unlabeled and the algorithms learn to the inherent structure from the input information[10].
a) *Clustering:* A clustering problem can be used where we want to discover the inherent groupings in the data, such as grouping customers by purchasing behavior.

b) *Association:* An association rule, learning problem can be used where was want to discover rules that describe large portions of your information , such as people that buy a also tend to buy b. Some popular examples of unsupervised learning algorithms are:k-means for clustering problems and apriori algorithm for association rule learning problems.

3) *Semi-supervised learning:* In this method, some information is labeled but most of it is unlabeled and a mixture of supervised and unsupervised techniques can be used[11]. A good example is a picture collection where only some of the pictures are labelled, (e.g. lion, dear, human) and the majority are unlabeled. The workflow of machine learning are given in the Fig3.

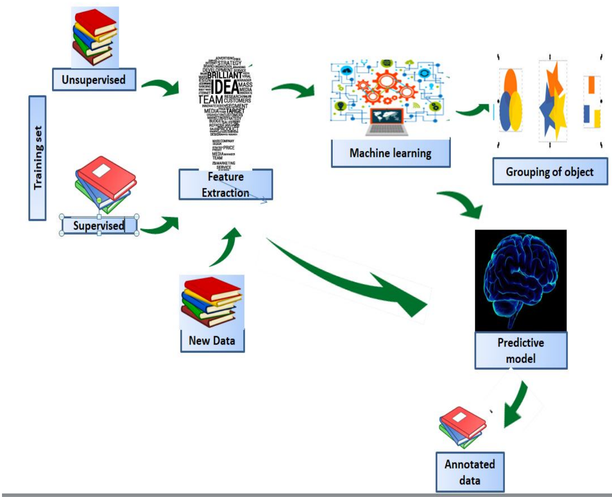

Fig3. Machine Learning Work Flow

4) *Reinforcement learning:* The algorithm is trained to map action-to-situation so that the reward or feedback signal is maximized[11]. To choose the action , classifier is not programmed directly , but instead trained to find the most rewarding actions by trial and error.

5) Transduction: Though it shares similar traits with supervise learning, but it does not develop a explicit classifier.

6) *Learning to learn:* The classifier is trained to learn from the bias, it induced during the previous stages. It is essential and efficient to organise the machine learning algorithms with detail to learning methods when one essential to consider the importance of the training information and select the classification rule that deliver the larger level of accuracy.

III. CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural networks take advantage of the underlying structure in images. Topological data, i.e., spatial data about the structure in an picture, such as adjacency and cycles are also taken into account[12]. We shall now look into the details of how the different layers of a convolution neural network communicate with each other.A convolution neural network involves of several layers defining different operations each of which are explained in the following subsections:convolutional layers , pooling layers,Normalization layers and fully connected layers .

1) *Convolutional layers:* Neurons in the first hidden layer view only a little picture window, and learn low-level highlights[13]. Those in deeper layers see bigger parts of the picture, and are able to learn more expressive highlights by joining low-level ones.Each layer is described by a couple of hyper-parameters: the number of filters to learn, their spatial support, the stride between various windows and an optional zero-padding which controls the size of the layer output

2) *Pooling layers:* this layer decreases the size of the input layer through some local non-linear operations, for example max(), so as to reduce the number of parameters to learn and provide some translation invariance[14]. The most relevant hyper-parameters are the help of the pooling window and the stride between various windows.

3) *Normalization layers:* Inspired by inhibition schemes present in the real neurons of the brain. This layer aims at improving simplification. They are normally used with sigmoid neurons (not by ReLU method).

4) *Fully-connected layers:* These layers are normally utilized as the last few of layers of the network[13]. By evacuating constraints, they can better summarize the data conveyed by lower-level layers in view of the final choice. Despite full connectivity, their complexity is still affordable due to the previous size reducing layers.

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IV. DEEP LEARNING NEURAL NETWORKS[DLNN]

Deep Learning is a type of Neural Network Algorithm that takes an input and process the information through some layers of the nonlinear transformation of the input information to process the output. L. Gueguenet al [15] stated that Deep learning algorithm has a unique feature that automatically extract the relevant features required for the solution of the problem. It decreases the burden on the developer to select the features explicitly. It can be used to solve the challenges of supervised, unsupervised or semi-supervised type[16].Fig4. shows the workflow of Deep Learning.

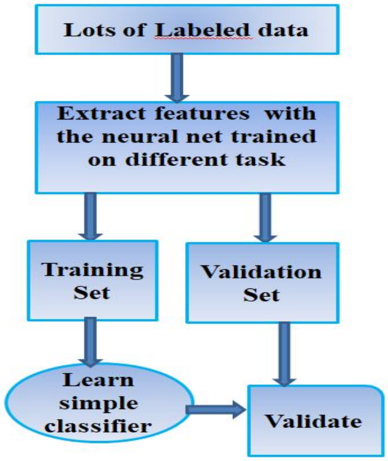

Fig4. Deep Learning WorkFlow

A different point is that when unsupervised information is gathered, and machine learning is executed on it, physically labeling of information has to be performed by the human being. This method is time-consuming and expensive.To overcome this problem deep learning is introduced as they can identify the particular information[16].Fig.4 shows the workflow of deep learning.

V. REVIEW ON VARIOUS DATASETS USED IN DEEP LEARNING METHODS FOR SATELLITE IMAGERY CLASSIFICATION

A. SpaceNet

To train and experiment the framework, it uses the data provided by Topcoder's SpaceNet Challenge [17]. This dataset consists of 250 16-bit GeoTiff images collected by the DigitalGlobe Worldview-3 satellite.The images are all of Las Vegas and each image are delivered in 4 different layouts: gray scale, RGB, 8-band multi-channel and higher-resolution 8-band multi-channel. These images all cover a 200 meter x 200 meter area on the ground.SpaceNet dataset is broken up into 60% training, 20% validation, and 20% test.

B. RSC11 Dataset

RSC11 Dataset used three spectral bands including red, green, and blue. There are 11 complicated scene classes , including dense forest, grassland, harbor, high buildings, low buildings, overpass, railway, residential area, roads, sparse forest, and storage tanks[18]. The total dataset consist of 1,232 images and each class contains 100 images . Each image has a size of 512×512 pixels and a spatial resolution of 0.2 m.

C. DeepSat

The training of Deep Convolution neural network framework requires a large volume of computation, while the search space is huge. To find the optimized hyper-parameter in a reasonable time, the search of hyper-parameter is conducted on two subsets of DeepSat dataset. Each subset consists of 4,000 training images, and 1,000 testing images, that randomly pick from SAT-4 and SAT-6 [19].

1) *SAT-4: SAT-4 consists of a total of 500,000 image area covering four broad land cover classes. [19,1]These datasets contain all land cover classes rather than barren land, trees, grassland.80% of dataset (400,000 areas), were selected for training and the remaining 20%(100,000 area) for testing dataset. It makes sure that the training and test datasets fit to disjoint set of image tiles. Each image area size is normalized to 28×28 pixels. Once produced, both the training and testing datasets were randomized using a pseudo-random number generator .*

2) *SAT-6: SAT-6 consists of a total of 405,000 image area covering 6 land cover classes-barren land,trees,grass land, roads, buildings and water bodies. Total dataset are 324,000 images are selected as the training dataset and 81,000 images are selected as the testing dataset. [19,1]Comparable to SAT-4, the training and test sets were chosen from disjoint National Agriculture Imagery Program tiles. Once produced, the images in the dataset were randomized in the same way as that for SAT-4. The specifications for the different land cover classes of SAT-4 and SAT-6 were assumed from those used in the National Land Cover Data (NLCD) algorithm .*

D. ImageNet

ImageNet consists of about 15 million high-resolution labeled images separated in roughly 22,0000 categories[20]. The actual size of the training data set used in the contest consists of about 1.2 million images, and participants need to classify a test data set into 1000 distinct classes.This images contained in the database is retrieved through search engines and therefore can be considered as common multimedia data,where participants make use of a subset of this data set for training classification algorithms of their choice .

E. UC Merced Land-Use Dataset

Merced dataset that contains of 21 different classes. Each set contains 100 images, and each image measures 256x2 pixels[21]. The images were initially extracted from large images from the Unites States Geological Survey (USGS) National Map Urban Area Imagery collection for various urban areas around the country. The 21 land-use classes are: agricultural, airplane, baseball diamond, beach, buildings, chaparral, dense residential, forest, freeway, golf course, harbor, intersection, medium density residential, mobile home park, overpass, parking lot, river, runway, sparse residential, storage tanks, and tennis courts[22,23].

F. Brazilian Coffee Scene Dataset

The Brazilian Coffee scenes dataset includes satellite images with an infra-red band, and these are less related to that of ImageNet dataset. The dataset is classified into Coffee and Non-Coffee scenes. Each image measures 64x64 pixels which is cropped from SPOT satellite images over four counties in the State of Minas Gerais, Brazil: viz Arceburgo, Guaranesia, Guaxupe, and Monte Santo [24]. This dataset considered the green, red, and near-infrared bands because they are the most useful and representative ones for distinguishing vegetation areas. The documents of coffee crops were implemented manually by agricultural investigators. To be particular, the creation of the dataset is implemented as follows: coffee class consists of 80% coffee pixels where as non-coffee class consist of 15 %coffee pixels.

G. RIT-18

RIT-18 is a high-resolution standard, designed to estimate the semantic segmentation of Multispectral Imaging Systems, collected by an UAS.This collection of non RGB imagery has developed in popularity, particularly in precision agriculture, because it is more cost effective than manned flights and provides better spatial resolution than satellite imagery[25]. This cost savings allow the user to assemble information more often, which increases the temporal purpose of the information as well.

H. EuroSAT dataset

EuroSAT dataset consists of 27,000 labeled images with a total of 10 different classes.Each of EuroSat dataset image patches measure 64x64 pixels it contains 2000 to 3000 images[26]. In total, the dataset has 27,000 images.The 10 classes of images covered inthis dataset are Industrial, Residential ,Annual crop ,Permanent crop, River,Sea & lake ,Herbaceous vegetation , Highway, Pasture and Forest[26].

I. WHU-RS19 Dataset

The WHU-RS19 dataset consists of 19 scene classes, including airport, beach, bridge, commercial area, desert, farmland, football field, forest, industrial area, meadow, mountain, park, parking lot, pond, port, railway station, residential area, river, and viaduct[26]. The entire dataset contains 1,005 images and for each scene class there are about 50 images. The image sizes are 600×600 pixels[27]. WHU_RS19 dataset has also been broadly adopted to calculate different scene classification methods.

J. RSSCN7 Dataset

The RSSCN7 dataset contains a total of 2,800 images which are composed of seven scene classes: grass land, forest, farm land, parking lot, residential region, industrial region, and river/lake[21,28]. From Google Earth for each class, it collects 400images that are cropped on four different scales with 100 images per scale. Each image has a size of 400×400 pixels.

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K. SIRI-WHU dataset

SIRI-WHU dataset consists of 2,400 images with 12 scene classes. Each class consists of 200 images with a spatial resolution of 2 m and a size of 200×200 pixels[29]. The 12 land-use classes contain agriculture, commercial, harbor, idle land, industrial, meadow, overpass, park, pond, residential, river, and water[30]. Although this dataset has been tested by several methods,the number of scene classes is relatively small.

L. NWPU-RESISC45 Dataset

The NWPU-RESISC45 dataset contains of 31,500 Satellite imagergy images divided into 45 scene classes. Each class includes 700 images with a size of 256×25 pixels in the red green blue (RGB) color space[29,30]. The spatial resolution be different from about 30 m to 0.2 m per pixel for maximum of the scene classes except for the classes of island, lake, mountain, and snowberg that have lower spatial resolutions.Table 1: shows the dataset provides many more images per class, scene classes, total images, and image size in comparison with other available datasets for Satellite imagery classification.

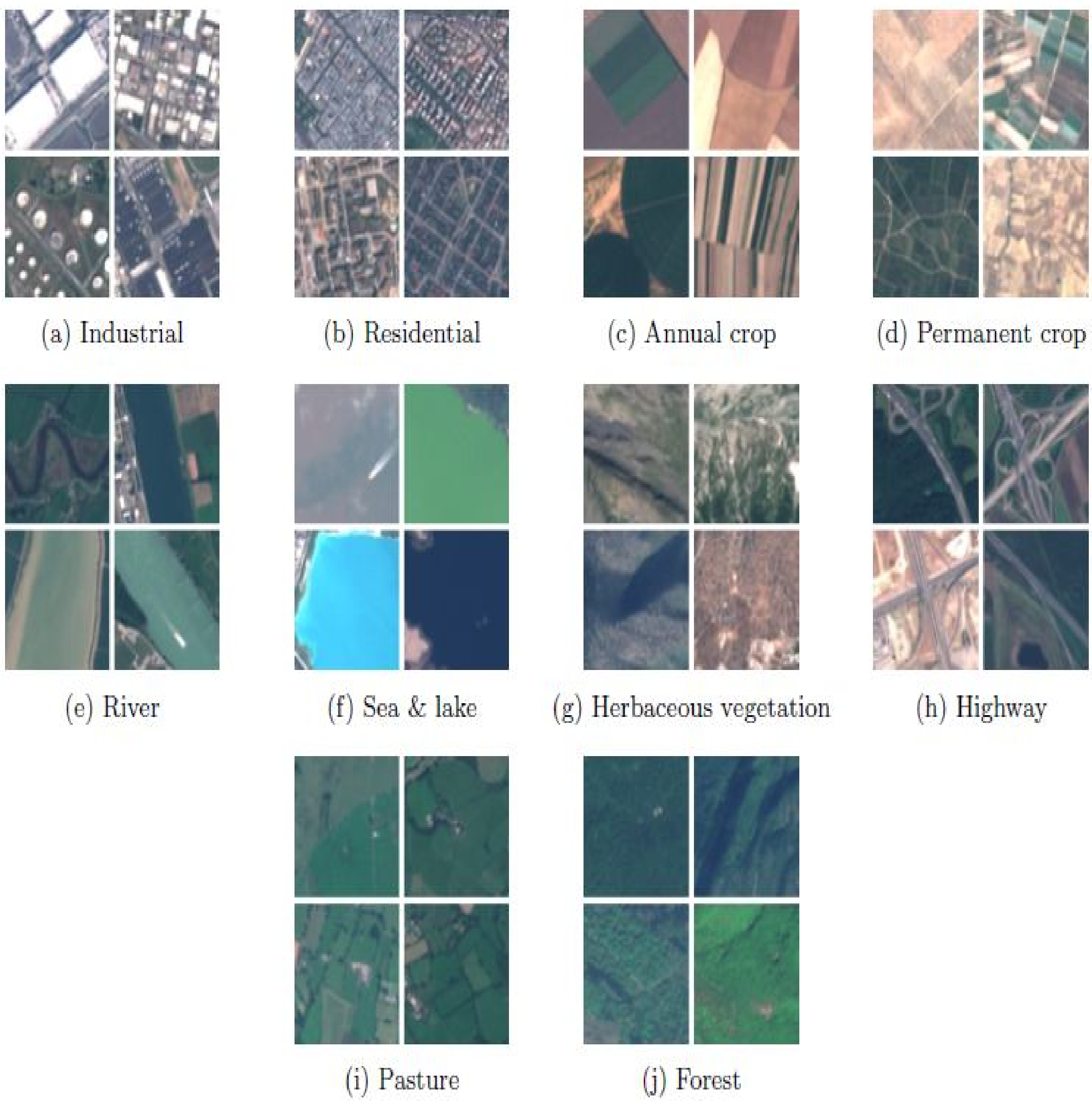

Fig5. This overview shows sample dataset images.[26,27,2,8,29]

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Table 1: Our dataset provides many more images per class, scene classes, total images, and image size in comparison with other available datasets for Satellite imagery classification.

S.No	Dataset	Total image	Scene class	Image size	Image per class
1	SpaceNet[17]	17355	1	650x650	50
2	RSC11[18]	1232	11	512x512	10
3	SAT-4[1,19]	50,000	4	28x28	100,00
4	SAT-6[19]	405,00	6	28x28	32400
5	ImageNet[20]	14000	2	256x256	50
6	UC Merced Land Use[21,22,23]	2100	21	256x256	100
7	Brazillian Coffee Scene[24]	2876	2	64x64	1438
8	EuroSat[26]	27000	10	64x64	2000
9	WHU-RS19[27]	50	19	600x600	50
10	RSSCN7[21,28]	400	7	400x400	400
11	SIRI-WHU[29,30]	2400	12	200x200	200

VI. CONCLUSION

Deep Learning approaches are practical for us to solve many problem in satellite imagery. This paper porpartes deep learning models and frameworks in detail.Deep learning has different kinds models and different type of dataset for satellite imagery. This paper presented a comprehensive review of the recent progress in the field of Satellite imagery scene classification, including benchmark datasets and state-of-the-art methods.

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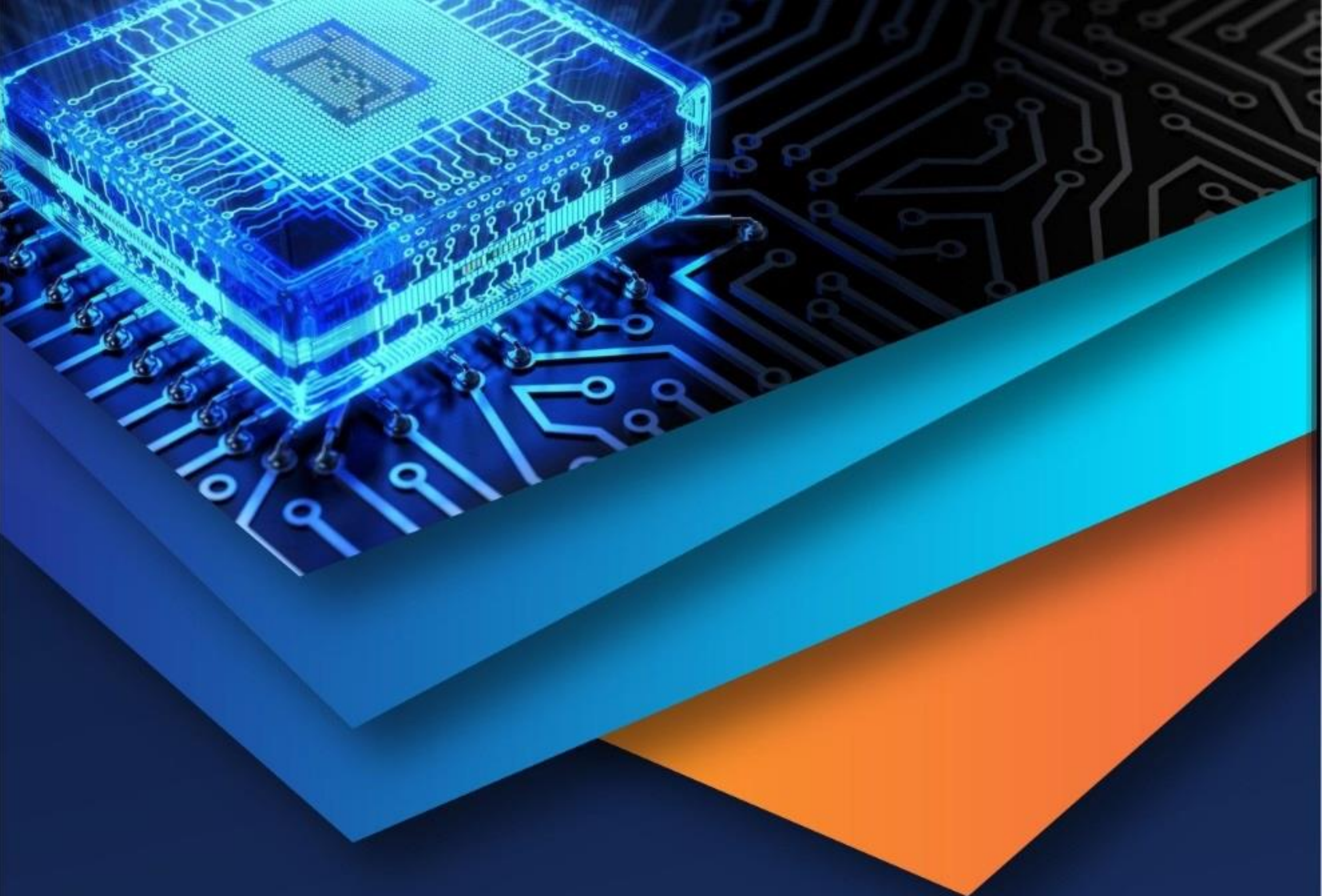

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