FORM 2

THE PATENTS ACT, 1970

(39 of 1970)

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COMPLETE SPECIFICATION

(See section 10 and rule 13)

Title: Object Classification for Remotely Sensed Images by using Enhanced CNN Model

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PREAMBLE TO THE DESCRIPTION:

The following specification particularly describes the invention and the manner in which it is to be performed.

(1) FIELD OF THE INVENTION

Satellite imagery is gaining ground in a variety of operations, including remote surveillance, environmental monitoring, and upstanding surveillance. All these operations, among other effects, calculate on satellite images to identify rudiments, events of interest and structures. In utmost operations, homemade object discovery and bracket becomes extremely delicate, especially when dealing with huge quantities of data and a large number of satellite images to be estimated at the same time. Although the discovery and classification of objects in images is a well-studied topic in the field of image processing, discovery in satellite (upstanding) images is more sensitive due to the tiny size of objects and the difficulty of shadowing and landing their visual properties. Several automatic discovery and bracket systems have been proposed and are presently being developed. Numerous algorithms have been introduced for feting and classifying objects in satellite prints, ranging from classic machine literacy (ML) to ultramodern deep literacy. In the once many decades, machine literacy algorithms for discovery and bracket have entered the utmost attention. These styles involve rooting multitudinous parcels from prints and classifying them using machine literacy classifiers. Due to the differences in the size, direction and background of the target object, automatic object discovery is still delicate. Traditional machine learning classifiers that calculate on homemade selection of functions, similar as Overeater, Gabor, Hough transfigure, gesture portions,etc. are unfit to attack the problems of automatic object discovery. As a result, an effective strategy is required, and Deep Learning has demonstrated promising results utilizing CNN to do the finding and bracketing task. Deep learning bracket approaches can learn features from prints instead of manually selecting them for automatic detection of high-perfection things that were recently printed. For the detection and bracketing of objects in satellite pictures, many deep literacy models based on convolutional neural networks (CNNs) have been created. There are two stages to these models. The existence of items in the image is respected in the first stage. Objects are categorized in the second step using a convolutional neural network.

(2) Description of the Invention-

This composition uses a custom convolutional neural network to classify and categorize items in satellite pictures. The model was taught to recognize three types of things in satellite images: trees, buildings, and vehicles. The outcomes of the discovery and bracketing are compared to the YOLO V3 algorithm's real performance on the same data set, as well as some standard reference data for other styles that haven't been performed. Unlike traditional CNN models, the YOLOV3 method combines object finding and categorizing in a single phase.

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(3) **BACKGROUND OF THE INVENTION**

This section looks at existing deep learning models for

detecting and classifying objects.

In their article, the authors [1] suggest a variant that uses a

CNN to acknowledge objects. They proposed a neural

convolution network supported rotating invariant areas

specifically for satellite images. The step of normalizing the

representation of features takes place before the classification

of objects begins to realize the concept of region (rotation

invariant) and specialize in it. this is often followed by

classification, which now depends on the very fact that every

image features a higher computational effort for the patch

results thanks to the invariant rotation sections.

The authors (2) mention a trend for discovering islands and massive crossings in bodies of water that may be detected in satellite pictures in their paper. Bodies of water, particularly gutters, must first be acknowledged or honored inside the image using recursive scanning, a method of determining specifics such as whether the body of water is a swash based on geometric limitations. The extent of the identified overflows is next checked to descry or identify pixels that will belong to a ground, using the information about the spatial bounds of numerous islands that was applied in the previous step. After the pixels have been honoured, an examination of their relationship or connectivity is performed to see if a ground member was honoured inside the image for the pixels that were linked initially. The requirement to grasp and need to know the spatial bounds of the items or structures to be identified, in this case islands, is a disadvantage of this technique.

The authors [3] describe a two-step method for recognizing road networks which will be seen or exist in aerial photographs captured by satellites or unmanned aerial vehicles (UAVs). It results in automatic detection by first performing a detection phase, followed by a felling or pruning phase. At this stage, a

Bayesian model is employed to classify the shapes of detected homogeneous or comparable characteristic regions or shapes. The second step involves employing a technique referred to as contingent probability to work out the probability that a given section or section may be a road. this system, like many others utilized in surveying, has a particularly high computational complexity.

The authors of [4] present an object-based image analysis technique for identifying land cover in satellite images, with attention on classification of the topology of various lengths of areas. we'd like to extract texture features before we will train an SVM classifier, which needs segmenting all of the objects within the image. Following that, these separated objects are wont to complete the extraction process. After recovering the textural features of the segmented objects, they're wont to train an SVM classifier to classify the land supported its cover and utilization. This technique's precision is restricted by feature extraction, which is usually limited and not comprehensive, complete, or precise in and of itself. The authors of [5] suggested a poorly supervised strategy for identifying objects in satellite images in their paper. The Boltzmann machine, a generative model with two basic tasks of encoding and decoding, is used. Encode's main purpose is to capture the features of each picture and communicate them to a Bayesian framework in order to improve object detection. For semi-supervised training, the Bayesian framework is supposed to be taught with data sets that comprise a sampling of pictures with objects labelled with independent labels. In the generators, a finite state machine and a deep CNN were combined (6). They'll need a well-developed literacy network that recognizes the worth of road segments extracted from satellite images. It's also typical to employ a trained deep CNN to categorize road segments with the help of photo patches. Combine the simplest fit set into a set of image batches to indicate the road network inside the images, using the problem of this deep CNN and commerce with a finite state machine. As a consequence, the proposed approach or design harvests road segments with significantly better accuracy by combining a finite state machine with deep CNN. This approach, still, suffers from an original issue therein it takes a substantial quantum of computer power to realize delicacy and is delicate to spot the image patches that stylish suit the end of the item being recognized.

The authors (7) used upstanding prints to trainer a deep literacy system to assay and honor damaged structures or structures. A CNN is trained specifically for this function employing a specialized data set of upstanding or satellite filmland of damaged structures that are incompletely or fully collapsed, unrepaired, abandoned, or with deficient systems. due to the huge quantum of knowledge involved, satellite filmland (VHR) have a high computational complexity. As a result, delicacy is likewise relatively high. The authors of (8) developed an optimized deep literacy network that aims to reduce the complexity associated with computation, which is found in many various classes and heterogeneous CNN models. The optimization is then for scene and image brackets in high spatial resolution remote-seeing filmland, which are often acquired by UAVs and satellite detectors and might be of current significant interest and utility. To estimate back processing complexity to the greatest quantum feasible, the most efficient technique for decreasing complexity was to use highly effective convolutional layers with a smaller kernel. This enhanced model is believed to be able of efficiently and reliably learning multiple characteristics so as to fulfil the task of scene categorization. The findings were positive, but farther optimization could be done to gauge back the time indeed quite the 40 twinkles laid out in the study for his or her operation.

(4) SUMMARY OF THE INVENTION:

The suggested deep learning model for item identification and categorization is depicted in Figure 1. Some of the important elements of the suggested solution are as follows:

i. Data collection and analysis

ii. Object Labeling and Data Preprocessing

iii. CNN training and construction

iv. CNN validation and analysis

v. Drawing of a bounding box

The labelling tool is used to classify images of houses, trees, and autos gathered from a collection of 3D satellite images. The annotated images are put into a convolutional neural network that has been customized. The personalized convolutional neural network's architecture is depicted in Figure 2 as well as the layer detail of the personalised convolutional neural network.

(5) BRIEF DESCRIPTION OF THE DRAWINGS

The proposed framework is shown in Figure 1. It takes AG Corpus dataset (text documents) as input and supports supervised learning process and produce classification results. The framework exploits both NLP and ML techniques. The former is used for pre-processing and feature engineering while the latter is used to perform learning-based document classification. Figure 2 shows the feature extraction process generated from the sequence of text with kernel size. Figure 4 and Figure 5 shows the feature engineering methods have little influence on the document classification models. Figure 6 training accuracy of the NN model is 98.54% whiles its variant with word embeddings, shown in Figure 7, exhibited 98.47% accuracy.

(6) DETAILED DESCRIPTION OF THE INVENTION

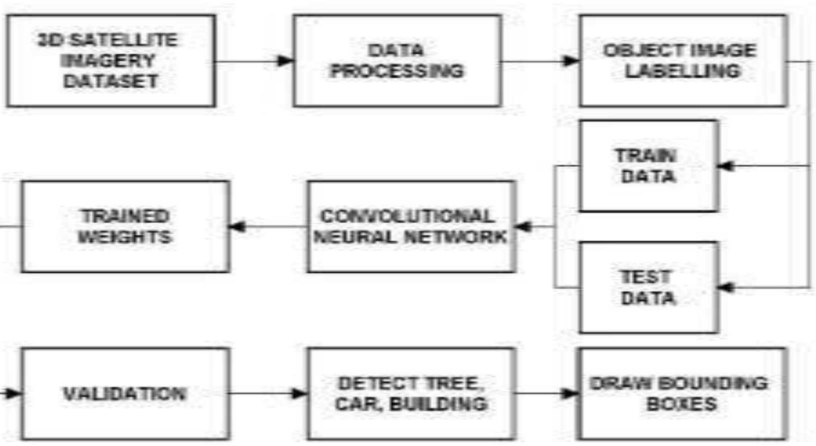

Figure 1: Architecture of the proposed system

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
	Convolutional	32	1 × 1	
1×	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
	Convolutional	64	1 × 1	
2×	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
	Convolutional	128	1 × 1	
8×	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
	Convolutional	256	1 × 1	
8×	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
	Convolutional	512	1 × 1	
4×	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 2: Proposed CNN architecture

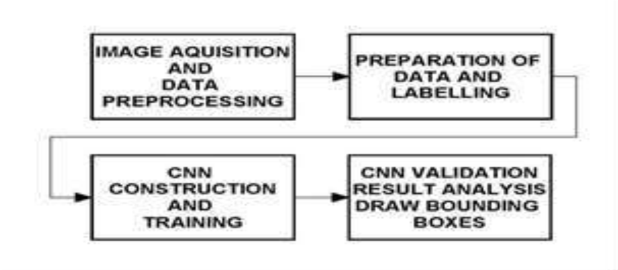

Figure 3: System Module

Figure 4: Result with 50-Epochs

Figure 4: Result with 100-Epochs

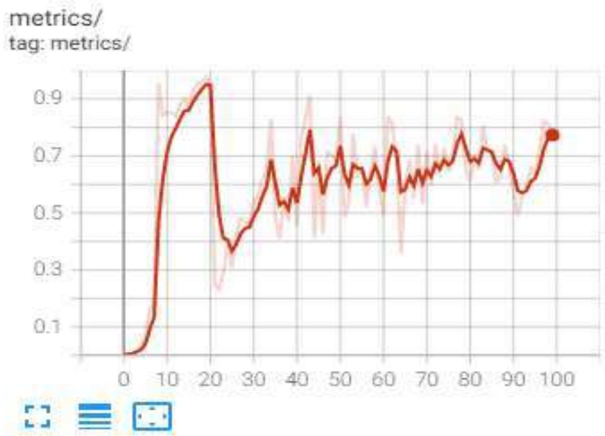

Figure 5: Accuracy of the system 100-epochs

Figure 6: Performance comparison among all document classification models

CLAIMS

We / I Claim:

1. The current research proposes an ensemble CNN model for linking and categorizing objects in satellite imagery.
2. The proposed technique was tested using three different items: a vehicle, a building, and a tree.
3. There are complications in the backdrop, size, noise, and distance concerns, object detection becomes considerably more difficult. So the proposed system can predict the from the sensed images.

Title: Object Classification for Remotely Sensed Images by using Enhanced CNN Model

ABSTRACT

Surveillance, military operations, geospatial surveys, and environmental impact and change monitoring are just a few of the applications for which satellite image analysis is becoming increasingly popular. The automatic detection and classification of objects might be a critical aspect of satellite image processing. Due to the nature and size of things, as well as the manner of visual elements, sleuthing and categorizing items in aerial pictures becomes difficult. Manual detection of objects in these photographs takes a lengthy time due to the nature and quantity of information obtained in these frames. It is necessary to implement the automated identification of various options or items from satellite pictures. Traditional object classification algorithms include two phases: (i) distinguishing areas within the image with the presence of things, and (ii) categorizing the objects in the regions. When there are complications in the backdrop, size, noise, and distance concerns, object detection becomes considerably more difficult. This study presents a novel convolutional neural network for identifying and categorizing three different types of objects in photographs: trees, buildings, and vehicles. It is also difficult to interpret and summarize the custom CNN's performance characteristics.