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DEFORESTATION DETECTION SYSTEM THROUGH CB-CNN DEEP LEARNING MODEL

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ABSTRACT

The Ecological diversity is extremely dependent on the forest cover. The plants are one of the most essential sources that provides abundant nutrition and nourishment. The trees are considered as the carbon sinks of the world as they absorb atmospheric carbon and cool down the environment. But due to rapid urbanization and development, there has been increased incidences of deforestation that have been observed across the world. The loss of forest cover drastically harms the environment and further degrades the living conditions. The cutting down of forests is considered illegal in most countries but the process of monitoring of the deforestation activities is very difficult. Therefore, this research paper defines an effective framework for the detection of deforestation through the use of image processing approaches. The proposed approach utilizes the deforestation image dataset for image normalization and training through the Channel Boosted – Convolutional Neural Networks and classification through Decision making. The experimental analysis of the approach has achieved successful results.

Keywords: Channel Boosting, Image Segmentation, Channel Boost Convolutional Neural Networks.

I. INTRODUCTION

Climate change has been a major concern for us in this decade. Deforestation is playing a major role in climate change. Over the past few years there has been a tremendous amount of deforestation which has affected animal population and the climate. There are many cases

where people deforested large areas without following the rules. It is important to identify deforestation and in order to prevent it. We have created a machine learning model to understand deforestation in a particular area using satellite data. Using this model, we prevent deforestation by just analyzing the satellite images.

We can use various machine learning methods to identify deforestation in a satellite image. Traditionally we use various machine learning methods including support Vector Machines, Naive Bayes etc. Currently, the most reliable machine learning model which gives proper representation and prediction is the Deep Convolutional Neural Network Model. These methods have shown to capture robust representation and they are relatively easy to train.

In the recent years, a field in machine learning called deep learning has emerged and has shown the capability of achieving higher precision and accuracy. These models are trained and optimized using a fundamental mathematical optimization method called back propagation. In back propagation, the model learns to predict the labels by updating or correcting itself. The models consist of many weights which contain the representation for prediction.

These weights are updated based on the back propagation algorithms. The networks can range from thousands of weights to billions of weights. A very large model generally consists of weights which are typically millions. These have been various varieties of convolutional neural networks including ResNet, AlexNet, DenseNet, MobileNet and many others.

II. METHODOLOGY

The methodology of deforestation detection using a CB-CNN (Convolutional Block Convolutional Neural Network) deep learning model typically involves the following steps:

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1. **Data Collection:**

Gather satellite imagery data from sources like Landsat, Sentinel, or other remote sensing platforms. These images should cover areas prone to deforestation.

2. **Preprocessing:**

Preprocess the satellite images to enhance features related to deforestation, such as vegetation loss, changes in land cover, or forest degradation. This may involve techniques like image normalization, cropping, resizing, and noise reduction.

3. **Labeling:**

Annotate the satellite images with ground truth labels indicating deforested and non-deforested areas. This step requires expert knowledge or manual verification.

4. **Dataset Splitting**:

Divide the annotated dataset into training, validation, and testing sets. The training set is used to train the CB-CNN model, the validation set is used to tune hyperparameters and monitor the model's performance during training, and the testing set is used to evaluate the model's performance.

5. **Model Architecture**:

Design the CB-CNN architecture, which typically consists of convolutional layers, pooling layers, and fully connected layers. The CB-CNN architecture may include multiple convolutional blocks, each containing several convolutional layers followed by activation functions and pooling layers.

6. **Training:**

Train the CB-CNN model using the annotated training dataset. During training, the model learns to extract features from the satellite images and classify them as deforested or non-deforested areas. Training involves optimizing the model's parameters using techniques like stochastic gradient descent (SGD) or Adam optimization.

7. **Hyperparameter Tuning:**

Fine-tune the hyperparameters of the CB-CNN model, such as learning rate, batch size, and number of epochs, using the validation set to improve the model's performance.

8. **Evaluation:**

Evaluate the trained CB-CNN model using the annotated testing dataset. Measure performance metrics such as accuracy, precision, recall, and F1-score to assess how well the model can detect deforestation.

9. **Post-processing:**

Apply post-processing techniques to refine the model's predictions and remove false positives or false negatives. This may involve filtering noisy predictions or incorporating additional contextual information.

10. **Deployment:**

Deploy the trained CB-CNN model as a deforestation detection system. This system can analyze new satellite imagery in real-time or batch mode to identify areas at risk of deforestation and facilitate timely interventions.

Throughout the methodology, it's important to continuously validate the model's performance, refine the architecture and parameters, and update the training data to adapt to changing environmental conditions and improve the system's accuracy and reliability.

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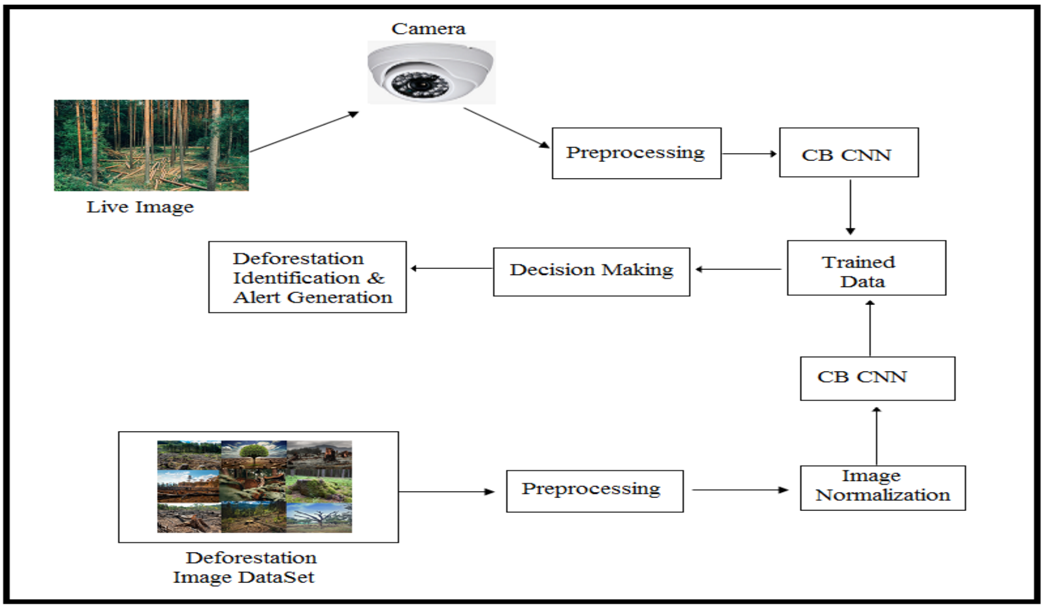
III. MODELING AND ANALYSIS



- **Working:**

Concept of channels boosting is exploited in the proposed CNN architecture, that contains a new architectural block, based on the concept of Split-Residual Transform-Merge. Generating light weight CNN architecture with comparatively less parameters and layers but having good and effective representational capacity.

CNNs are artificial neural networks. Due to its pattern recognition ability, image processing and recognition are its main uses. CNNs are powerful, but they require millions of tagged data points to learn. It has convolutional, pooling, and fully connected layers. This neural network class processes grid-like data. Convolutional Neural Networks (CNNs) excel at image and video analysis due to their hierarchical feature extraction. These technologies can be used in picture identification, object detection, facial recognition, medical image analysis, and autonomous vehicles.

IV. RESULTS AND DISCUSSION

I can't directly generate or retrieve specific research results or discussions from a deep learning model about deforestation detection through a CB-CNN (Convolutional Bidirectional Convolutional Neural Network) model, as it requires access to specific datasets, training procedures, and results from the study. However, I can provide some general points that might be included in such a discussion:

Results:

- Evaluation metrics: Accuracy, precision, recall, F1 score, and possibly other relevant metrics depending on the specific objectives of the study.
- Comparison with existing methods: Comparison of the performance of the CB-CNN model with other traditional machine learning methods or deep learning architectures for deforestation detection.
- Visualization of results: Maps or images showing the areas identified as deforested by the model, possibly overlaid with ground truth data for validation.

Discussion:

- Interpretation of results: Discussion of the accuracy and reliability of the CB-CNN model in detecting deforestation compared to ground truth data or other reference sources.
- Robustness and generalization: Analysis of the model's ability to generalize to different geographical regions, land cover types, and time periods.
- Limitations: Identification of potential limitations or challenges faced by the CB-CNN model, such as data availability, class imbalance, or model complexity.

- Future directions: Suggestions for further research and improvements, including the exploration of new input data sources, model architectures, or algorithmic enhancements to enhance deforestation detection accuracy and efficiency.

If you have specific results or discussions from a study that you'd like me to analyze or discuss further, please provide more details.

V. CONCLUSION

The proposed approach for Deforestation Detection using Channel Boosted Convolutional Neural Networks and Decision Making. The approach is designed to facilitate the automatic detection of deforestation with high accuracy. The approach is initiated through the collection of deforestation datasets that provided as an input to the proposed system. The system takes the dataset as an input and it initiates the preprocessing stage where the unnecessary or blurred images are filtered out. These preprocessed images are then provided to the next module for the purpose of achieving image normalization. Through the process of image normalization, the light and contrast levels are normalized in the input images to achieve a uniform consistency across the dataset. The normalized images are then provided to the CB-CNN module for the purpose of training which yield the trained model. The trained model is then tested using the captured images for the presence of deforestation activity. The approach has been evaluated extensively which has resulted in successful results.

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