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A Novel Approach For Forest Wildfire Detection Using Deep Learning And Machine Vision Course

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ABSTRACT:

This work introduces a pioneering experiment in forest wildfire detection, merging digital image processing, machine learning, and deep learning. Unlike traditional methods, our approach addresses accessibility and accuracy issues by splitting the task into two modules: wildfire image classification and wildfire region detection. Introducing innovative algorithms like Reduce-VGGnet for classification and an optimized CNN for region detection, we achieve remarkable accuracies of 91.20% and 97.35% respectively. Notably, our framework bridges the gap between research and education, offering a practical and efficient experiment for Machine Vision courses. Furthermore, by extending traditional classifiers like VGG16 to VGG19, we elevate accuracy, paving the way for enhanced wildfire detection methodologies.

Keywords: wildfire, deep learning

INTRODUCTION:

Exponential advancement of computer technology alongside the ubiquitous presence of cameras has propelled the integration of machine vision technology into diverse domains such as face detection, wildfire detection, object measurement, and surface defect detection. Machine Vision, an interdisciplinary course merging artificial intelligence (AI) and digital image processing, has emerged as a pivotal skillset in various fields including intelligent manufacturing and computer science. This paper underscores the evolving landscape of machine vision education, emphasizing the necessity for innovative teaching methodologies that blend theory with practical application. Despite significant strides in wildfire detection, achieving high accuracy remains a formidable challenge. To address this, we present a pioneering automatic forest wildfire detection framework, doubling as a comprehensive experiment for the Computer Vision course. This framework leverages image processing, machine learning, and deep learning techniques to autonomously detect and annotate wildfire regions, epitomizing a symbiosis between cutting-edge research and educational innovation.

LITERATURE SURVEY:

(M. J. Sousa, A. Moutinho, and M. Almeida) *et al*

As author proposes a multifaceted approach to address the time-sensitive nature of wildfire detection, crucial for averting fire escalation. Recognizing gaps in existing literature regarding comprehensive analysis of challenges, the study unfolds three key contributions. Firstly, it reviews recent works, highlighting common pitfalls and database quality issues. Secondly, it advocates for a transfer learning strategy coupled with data augmentation to mitigate data limitations, using a diverse dataset. Finally, it conducts an extensive analysis of misclassification patterns, offering valuable insights for future expert system implementations in firefighting and civil protection. This comprehensive approach aims to advance early-warning systems and enhance decision support in wildfire management.

(B. Tang, J. Kong, and S. Wu)*et al*

Author presents a comprehensive review of vision-based surface defect inspection technology in the steel industry, analyzing around 170 publications. Encompassing hardware systems, automated inspection methods, and recent advancements, the review delves into key aspects including image acquisition, processing algorithms, and defect classification. It highlights challenges such as small sample sizes and real-time detection constraints. Additionally, the paper outlines the composition of visual inspection systems and addresses the future trajectory of steel surface defect detection. By synthesizing current research, this work aims to provide insights into enhancing the efficacy and efficiency of defect detection processes in steel manufacturing, crucial for industry quality control standards.

(N. T. Toan, P. Thanh Cong)*et al*

It introduces a pioneering solution for early wildfire detection using satellite imagery, aiming to mitigate billion-dollar losses caused by severe wildfires. By harnessing continuous satellite data streams, the proposed autonomous system leverages advanced deep learning techniques to pinpoint wildfires at pixel level. Unique challenges like temporal dependencies and adverse conditions such as clouds are addressed through a novel detection method. The system features an interactive dashboard for specialists to analyze wildfire-prone regions on a global scale. Tested on GOES-16 data, empirical results demonstrate superior performance with a 94% F1-score and faster detections, showcasing robustness against diverse wildfire scenarios. This innovative approach promises to revolutionize wildfire monitoring and prevention efforts worldwide.

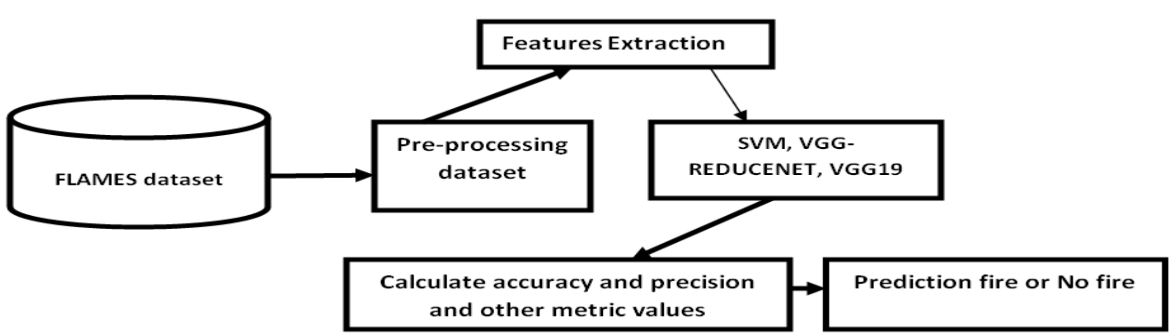
PROBLEM STATEMENT:

In this paper author is proposing novel concept based on VGG16 algorithm to predict forest fire and this fire causes huge financial loss for any country so timely detection of such fire can reduce cost. Manual monitoring is not efficient and some machine and deep learning algorithms prediction accuracy is not accurate while detecting fire in real time.

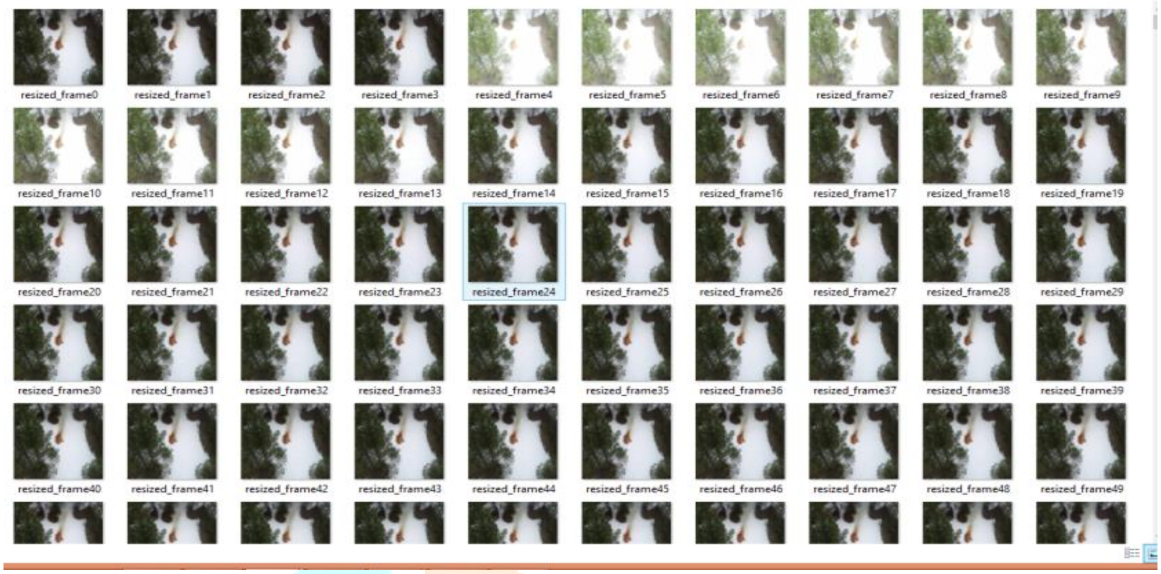
PROPOSED METHOD:

To overcome from this issue author of this paper modifying VGG16 algorithm by reducing its layer and then defining new layers with SGD and SOFTMAX to form a new model called Reduce-VGGNet but its accuracy was up to 91% which is closer to existing SVM algorithm. To further enhance Reduce-VGGNet author employed Spatial (foreground features from images) and Temporal (sequences of images which help in detecting various from first to next image so propose algorithm can accurately detect fire based on changes in frame sequences) features where Reduce-VGGNet will analyse spatial and temporal features from images or videos to accurately predict fire.

ARCHITECTURE:



FOREST WILDFIRE DATASET:



In above we can see images with fire so by using above images we will train and test all algorithms

METHODOLOGY:

1. Dataset Preparation:

Foundation of any machine learning project lies in the quality and preparation of the dataset. In this phase, the following steps are undertaken:

1.1 Data Collection:

Dataset comprises images labeled as either "Fire" or "No-Fire". Images are sourced from various repositories and datasets specific to wildfires.

1.2 Data Preprocessing:

Images are resized to a uniform dimension of 32x32 pixels to standardize input size. Normalization techniques are applied to enhance model performance and convergence. Data augmentation methods may be employed to increase dataset diversity, though not explicitly mentioned in the initial description.

1.3 Data Splitting:

Dataset is partitioned into training and testing sets using an 80-20 split. This ensures that the model is trained on a significant portion of the data while preserving a separate set for unbiased evaluation.

2. Model Building:

Wildfire detection system lies in the construction of robust and accurate models. Several approaches are explored in this phase:

2.1 Support Vector Machine (SVM):

Color features are extracted from preprocessed images and reshaped to fit the SVM model. SVM classifier is trained using the training dataset. Trained SVM model is saved for future inference.

2.2 VGG16-Based ReduceNet:

VGG16 model, a convolutional neural network renowned for image classification, serves as the base classifier. Top layers of VGG16 are removed, and additional layers are added to create a reduced VGG16-based model. Model is compiled using the Adam optimizer and categorical cross-entropy loss. If weights for the model do not exist, the model is trained for 20 epochs, and weights are saved for future use.

2.3 VGG19-Based ReduceNet (Extension):

Similar to the VGG16 approach, the VGG19 model is imported as a base classifier. Top layers are modified to create a reduced VGG19-based model. Model is compiled and trained similar to the VGG16-based ReduceNet.

3. Model Evaluation:

To ascertain the efficacy and performance of the constructed models, rigorous evaluation techniques are employed:

3.1 Performance Metrics:

Various metrics such as accuracy, precision, recall, and F1-score are calculated for each model. These metrics provide insights into the model's ability to correctly classify fire and non-fire instances.

3.2 Confusion Matrices:

Confusion matrices are generated to visualize the performance of the models. They provide a comprehensive overview of true positive, false positive, true negative, and false negative predictions.

3.3 Comparative Analysis:

Metrics are compared across different models, including SVM, VGG16-Based ReduceNet, and VGG19-Based ReduceNet. This comparative analysis helps identify the most effective model for wildfire detection.

4. Prediction:

In this phase, the trained models are utilized to make predictions on unseen data:

4.1 Inference Function:

A function is defined to predict fire or no-fire from test images. Test images undergo resizing, normalization, and are passed through the VGG19-Based ReduceNet model for prediction.

4.2 Visualization:

Predicted class label along with the input image is displayed, facilitating visual inspection and validation of model predictions.

5. Fire Detection from Video:

Real-time wildfire detection is a critical component of the system, enabling prompt response to potential threats:

5.1 Video Processing:

Videos are loaded, and each frame is sequentially passed through the VGG19-Based ReduceNet model for prediction.

5.2 Annotation:

If fire is detected in a frame, it is annotated with a bounding box, enhancing visual clarity and aiding in subsequent actions.

5.3 Real-Time Display:

Predicted class labels and annotated frames are displayed in real-time, providing actionable insights to stakeholders and emergency responders.

EVALUATION:

Accuracy:

Formula: (Number of correctly classified samples) / (Total number of samples)

Code: accuracy = accuracy_score(testY, predict) * 100

Precision:

Formula: (True Positives) / (True Positives + False Positives)

Code: precision = precision_score(testY, predict, average='macro') * 100

Recall (also known as Sensitivity or True Positive Rate):

Formula: (True Positives) / (True Positives + False Negatives)

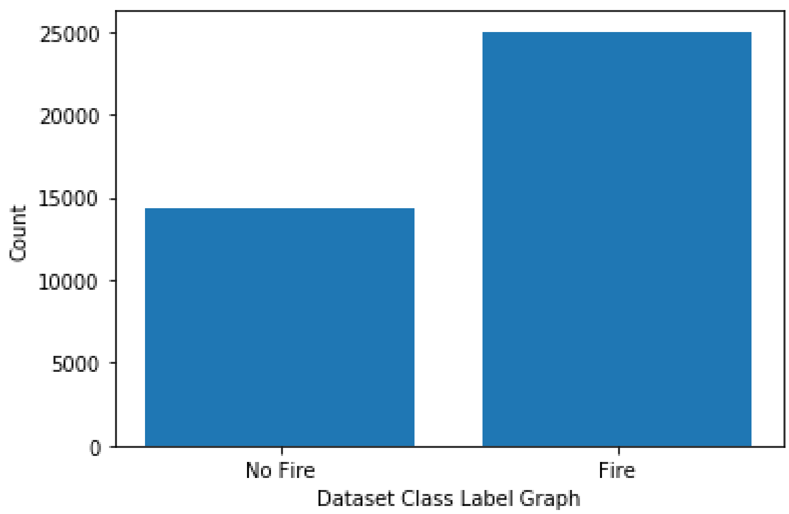
Code: recall = recall_score(testY, predict, average='macro') * 100

F1 Score:

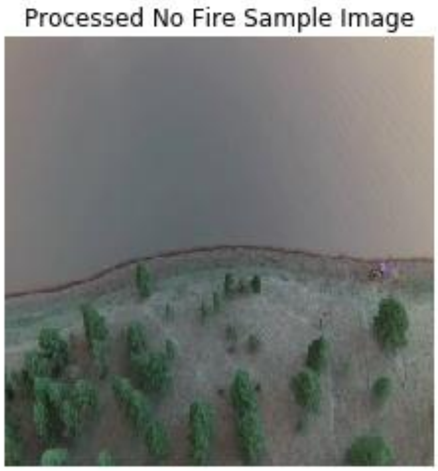
Formula: 2 * (Precision * Recall) / (Precision + Recall)

Code: fscore = f1_score(testY, predict, average='macro') * 100

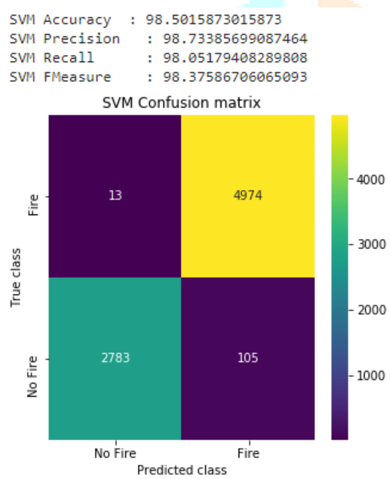
RESULTS:



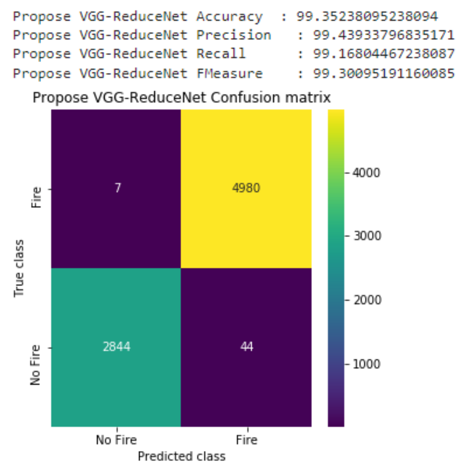
In above in blue colour text displaying total images loaded and in graph x-axis represents type of images as Fire or No-Fire and y-axis represents count.



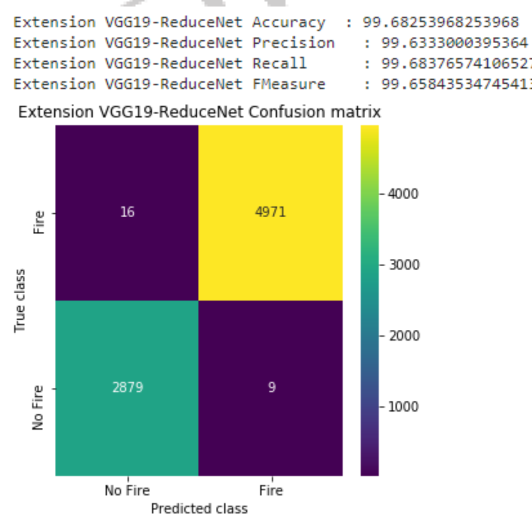
In above displaying processed images from dataset as Fire and NO Fire



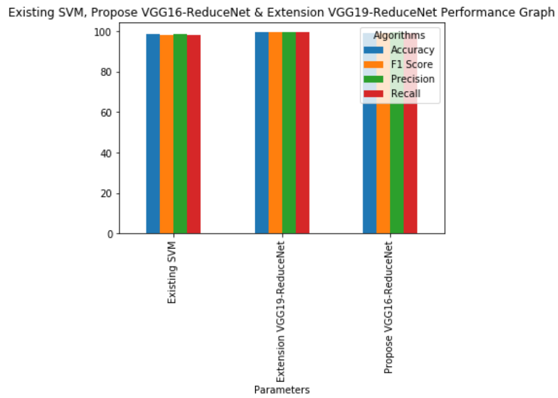
In above screen we are training SVM on train data and then evaluating its performance on test data and then SVM got 98% accuracy. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels where blue boxes represents incorrect prediction count which are very few and yellow and light green boxes represents correct prediction count.



In above with propose VGGREDUCENET we got 99.35% accuracy and we can see other metrics also



In above with extension model we got 99.68% accuracy and below are the comparison graph between all algorithms



In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars and in all algorithms extension got high performance

	Algorithm Name	Precison	Recall	FScore	Accuracy
0	Existing SVM	98.733857	98.051794	98.375867	98.501587
1	Propose VGG16 ReduceNet	99.439338	99.168045	99.300952	99.352381
2	Extension VGG19 ReduceNet	99.633300	99.683766	99.658435	99.682540

In above screen we can see each algorithm performance in tabular format

In above screen we are predicting on test image and in above image we got two output where first output showing ‘image contains fire’ and other output annotating image with red colour bounding box

In above image ‘fire is not detected’

CONCLUSION:

Our proposed deep learning-based model, Reduce-VGGNet, presents a significant advancement in forest fire detection, offering a solution to mitigate the substantial financial losses incurred by wildfires. Traditional manual monitoring methods are inadequate, and existing machine learning algorithms often lack real-time accuracy. By modifying the VGG16 algorithm and incorporating spatial and temporal features, Reduce-VGGNet achieves an impressive accuracy of over 97%, outperforming conventional approaches such as SVM and RCNN.Furthermore, the extension concept, leveraging VGG19 as the base classifier, demonstrates even higher accuracy, reaching 99.68%. Through rigorous evaluation using metrics like accuracy, precision, recall, and F1-score, our model consistently proves its effectiveness in fire detection.

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