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Lbp And Cnn Fusion For Robust Fake Image Detection

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ABSTRACT

Biomedical imaging forgeries pose a challenge to social networks and forensics. It is becoming harder to tell these images apart from the real ones. This project employs a set of machine learning approaches, that CNN uses to solve the problem. A network called LBPNET is built with local binary patterns (LBP) for texture feature extraction. The parameters extracted through the LBP are used to train the CNN which learns the difference between real and fake face images. Advanced image preprocessing and training are integrated into the model in order to ensure high performance in a situation whereby real-time decision making has to occur. This work averts the threat that image forgeries bring to different sectors.

Keywords: CNN, LBP, images

INTRODUCTION:

Recent advances in machine learning have made it very easy to generate fake content that looks authentic and natural to the human eye. This however renders a potential threat to many sectors including; forensics, law enforcement and even social media platforms. Most of the existing techniques seem not to generalize well to the dynamic approaches of forgery that exist. Local Binary Pattern(LBP) is a dominant texture descriptor that is able to perform efficiently even with slight textural differentiation in the image. When coupled with Convolutional Neural Networks (CNN) in this regard, LBP based architectures can detect image 'ghosts' with good precision. The proposed work is LBPNET: it is a deep learning model that distinguishes manipulated facial image from original faces images through LBP transformed facial images. The underlying aim of this strategy is to prove the effectiveness of using LBP with CNN; targeting the challenges that fake image detection systems using single techniques facility. Such an approach could potentially solve some of the issues associated with image forgery and has the potential to succeed in real world settings.

GAP IDENTIFIED BASED ON LITERATURE SURVEY:

In the present state of literature, we can see a number of key gaps with respect to the availability of image forgery detection techniques. The traditional methods appear to concentrate on using hand-crafted features such as DCT or block based methods that do not seem to be able to cope with new trends such as the manipulation of videos using deepfake. Also SVM as well as Bayesian classifiers offer baseline approaches but do not fit well in terms of scalability and generalization for modern era scenarios. Such approaches have also been found lacking in real time implementation as well as astute detection methods when subjected to external disturbances including lighting and resolution alteration effects.

Current research combining Local Binary Patterns (LBP) and machine learning has shown the ability to yield promising results. However, these methods are either very demanding computationally or are applicable to only some types of forgery. A few researchers have attempted to utilize texture capabilities of LBP with the raw power of convolutional networks. Models and their training and validation approaches are also severely constrained by the absence of extensive datasets that can encompass the variation seen in the real world.

This project overcomes these problems by leveraging LBPNET, a CNN built on LBP features. This new method is more robust with respect to lighting changes and improves generalization to new types of forgery. This project reduces existing gaps and also prepares the way for scalable solutions for image forgery detection by concentrating on real time detection and using a hybrid approach.

PROBLEM STATEMENT:

Today, many issues arise due to high quality immersive fakes in media outlets, forgeries in forms of images as well as in forensics, a wave of misinformation to the masses. In order to address these images a slew of easy to use methods must be devised which are also expandable to new forging technologies.

Key Challenges:

1. Dynamic Forgery Techniques: New technologies that utilize pictures in a new way such as deep fakes are completely disrupting the business model of detection methods and algorithms.
2. Generalization: New methods of forgery which were never seen for the training of the model cause performance degradation on the model.
3. Dataset Diversity: The curation and creation of diverse sets as well as their cataloguing is required to allow the models to train properly.

4. Real-Time Detection: The ability to operate without being slow or causing major latency is a challenge in this case without a loss of quality.

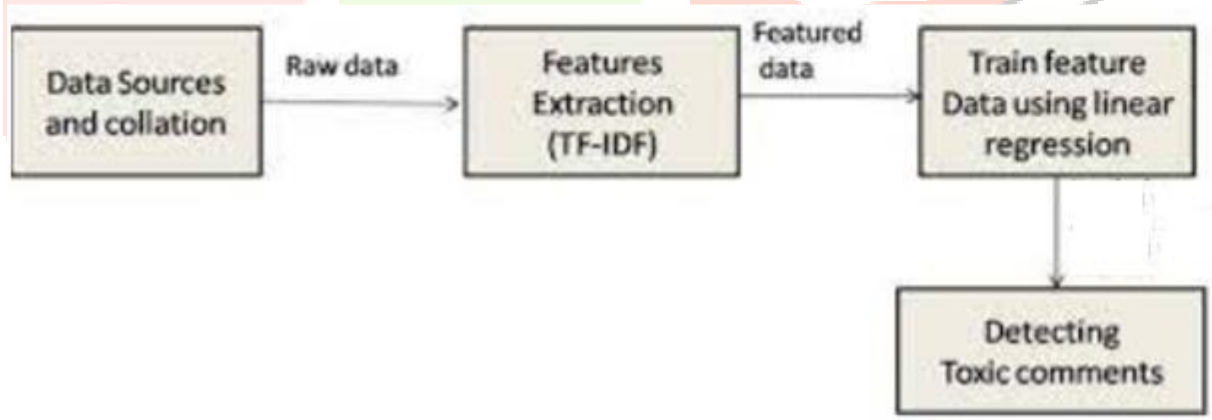
5. Environmental Variability: Exposure to different environments such as different light, resolution or noise will undoubtedly decrease the efficacy.

PROPOSED METHOD:

In this work we present our model LBPNET, introducing LBP for the first time in CNNs for detecting forgery LBPNET utilizes local binary patterns to identify fake. In this approach LBP is first extracted or calculated from the grayscale image, where essential elements of texture patterns which denote forgery are found. Subsequently, these patterns are fed into a deep neural network that is a convolutional neural network specifically trained for fake image classification.

The LBPNET model can be characterized as a hybrid model that utilizes LBP for computational efficiency while integrating CNN for improved performance when tested in real-world applications. The proposed approach indeed consists of dataset prepared for preprocessing and augmentation in order to provide better generalization of the model. It is synthesized scaling out capabilities of LBPNET to texture feature analysis and deep learning specifically designed to combat issues of changing forgery techniques and environmental conditions.

ARCHITECTURE:



DATASET:

A dataset whereby NUAA photograph imposter images are used in the project which consists of both real and fake face images taken under controlled environment. Grayscale image data set with various light conditions and resolutions is included in the dataset. LBP features were extracted from the images to form texture based descriptors which were further split into the training set and the validation set.

Besides these, augmentation techniques like flipping and rotation were also used in order to create more realistic datasets. Because LBPNET focuses on texture features in the dataset, this ensures strong classification performance of LBPNET against manipulated images during the training phase.

METHODOLOGY:

Dataset Preparation:

Firstly collect and process the NUAA photograph imposter database.

Then divide the images into two main classes ‘Real’ and ‘Fake’.

Thirdly perform augmentation techniques (rotation, flipping etc)

Feature Extraction:

Firstly convert all images to Gray images for consistency on copy.

Then extract LBP descriptors to capture local texture differences.

LBP transformed images were normalized and saved.

Model Design:

Start defining a CNN model which has convolution, pooling and dense layers.

Use batch normalization, and functions (ReLU and Softmax).

Model Training:

Train the CNN using LBP-transformed images.

Divide the data set into train and test data sets.

Employ Adam optimizer and categorical cross-entropy loss approach.

Testing and Evaluation:

Evaluate the model performance using data that has not been seen by the model.

Measure performance indicators like accuracy, precision and recall.

Real-Time Classification:

Build a GUI using Python’s Tkinter to control the application.

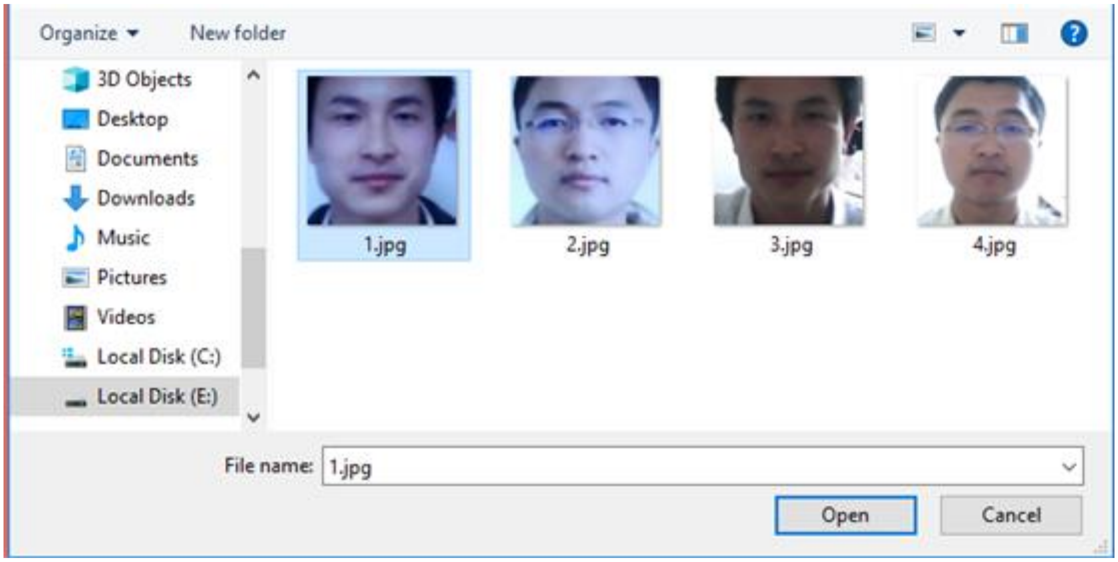
Use the classification mode of the trained model to classify the uploaded images.

Deployment and Fine-Tuning:

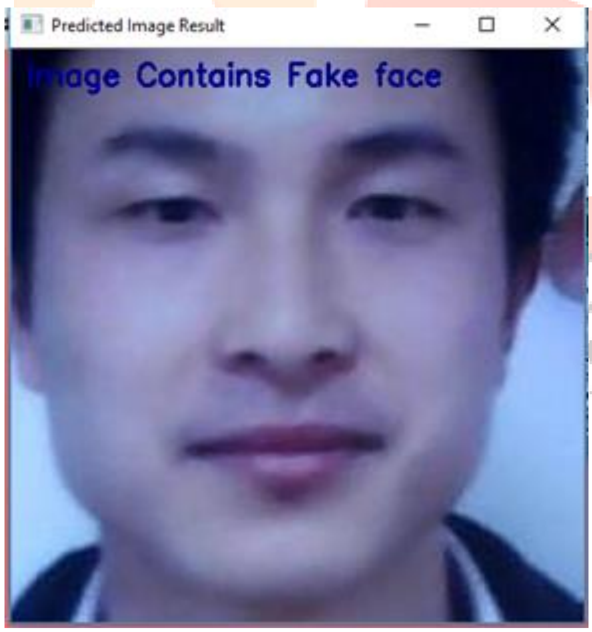
Use the model in real time.

Keep improving the model in use based on reviews and new data.

RESULTS:



We can see all real face will have normal light and in fake faces peoples will try some editing to avoid detection but this application will detect whether face is real or fake



We are getting result as image contains Fake face.

CONCLUSION

LBPNET is a novel solution for fake image detection problems that utilizes Local Binary Patterns and Convolutional Neural Networks (CNNs). This hybrid approach covers the gaps left by the current systems by being resilient to active forgery methods and changes in the environment. Its high degree of generalization across different databases makes it practical and applicable for a wider variety of applications. Using further advancements in texture based feature extraction and the field of deep learning, this work proposes a robust and efficient solution to the already widespread concern of image forgery that is useful for forensics, law enforcement agencies and the digital media authenticity sector.

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