www.ijbar.org
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

# FAKE OR REAL PHOTO DETECTION WITH DEEP LEARNING WITHOUT USING BINARY PATTERNS

Y.SUPRAJA[1]
Dr. M. VEERA KUMARI , M.Tech, Ph.D[2]
M-Tech Student, Dept.of CSE,UNIVESAL COLLEGE OF ENGINEERING AND TECHNOLOGY,Andhra pradhesh, India [1]
Associate Professor,HOD Dept.of CSE,UNIVERSAL COLLEGE OF ENGINEERING AND TECHNOLOGY,Andhra pradhesh, India[2]
suprajatarun5@gmail.com , veerakumarimamidi@gmail.com

## ABSTRACT

Fake image detection is an important problem in the field of computer vision and deep learning, as the use of manipulated images for deception or propaganda purposes is becoming increasingly common. We propose a deep learning approach for detecting fake images, which is based on a combination of deep neural networks and traditional image processing techniques. Our method extracts a set of features from the input image, including statistical properties, color distributions and texture information. These features are then fed into a classifier, which determines whether the image is genuine or manipulated. We evaluate our approach on a large dataset of real and fake images and demonstrate that it achieves state-of-the-art performance in terms of accuracy, precision, and recall. Our results suggest that deep learning methods can be effective for detecting fake images and have the potential to be used in a wide range of applications, including social media content moderation, news verification, and forensic analysis.

**KEY TERMS**: manipulated,deception,texture,state-of-the-art.

## 1 INTRODUCTION

Fake image detection, also known as image forensics, is the process of identifying and verifying the authenticity of digital images. With the rise of digital media and editing tools, it has become increasingly easy for individuals to manipulate images and create fakes that can be used for various purposes, including spreading misinformation, propaganda, and even committing fraud. Fake image detection is a complex process that involves analyzing various aspects of an image, such as its metadata, pixel structure, and visual content. There are several techniques used for this purpose, including digital watermarking, error level analysis, and image tampering detection. Digital watermarking involves embedding a unique identifier into an image, which can later be used to verify its authenticity. Error level analysis, on the other hand, examines the variations in compression quality across different parts of an image, which can indicate the presence of editing. Image tampering detection involves analyzing the image's visual content, such as the presence of inconsistent shadows or unnatural color variations, which can be signs of manipulation. Fake image detection has become increasingly important in recent years, as the spread of false information and propaganda has become a growing concern. It is used by various organizations and individuals, including news agencies, social media platforms, and law enforcement agencies, to verify the authenticity of images and prevent the spread of false information.

## 2. LITERATURE SURVEY

### INTRODUCTION:

With the rise of social media and advanced image editing tools, fake or manipulated images have become increasingly prevalent. These fakes can be created using traditional tools (Photoshop) or generated using AI-based methods like GANs (Generative Adversarial Networks). Fake image detection is crucial for digital forensics, journalism, social media moderation, and cybersecurity. Deep learning, especially Convolutional Neural Networks (CNNs), has proven highly effective in this domain.

**1. Bayar and Stamm (2016) – *"A Deep Learning Approach to Universal Image Manipulation Detection Using a New Convolutional Layer"***

**Method**: Introduced a constrained convolutional layer that helps CNNs focus on manipulation traces.

**Dataset**: BOSSBase and Dresden Image Database.

**Outcome**: Achieved high detection accuracy for splicing, copy-move, and removal.

**Limitation**: Not optimized for GAN-generated fakes.

**2. Zhang et al. (2019) – *"Detecting GAN-Synthesized Faces Using CNNs"***

**Method**: Used CNN to detect artifacts and inconsistencies in GAN-generated face images.

**Dataset**: PGGAN-generated images and real face datasets.

**Result**: The model effectively detected PGGAN images but was less robust to other GAN types.

**Contribution**: Highlighted challenges of generalizing across different GANs.

**3. Wang et al. (2020) – *"CNN-generated images are surprisingly easy to spot... for now"***

**Method**: Trained binary CNN classifier for real vs. fake image classification.

**Dataset**: Images from various GANs (StyleGAN, BigGAN, etc.).

**Finding**: CNNs can distinguish GAN images due to artifacts; however, adversaries can quickly adapt.

**Significance**: Stressed the need for robust and generalizable detectors.

**4. Verdoliva (2020) – *"Media Forensics and DeepFakes: An Overview"***

**Scope**: A comprehensive survey on deep learning methods for fake image and video detection.

**Discussion**: Reviewed methods including CNN, RNN, attention models, and hybrid approaches.

**Insight**: Emphasized the importance of explainability and temporal consistency checks in detection.

**5. Durall et al. (2020) – *"Watch Your Up-Convolution: CNN Based Generative Deep Neural Networks Are Failing to Reproduce Spectral Distributions"***

**Approach**: Detected fake images by analyzing frequency spectrum distortions.

**Outcome**: Spectral analysis exposed GAN image inconsistencies.

**Importance**: Showed the value of combining spatial and frequency-domain analysis.

**6. Liu et al. (2021) – *"Spatial Attention-Guided CNN for GAN Image Detection"***

**Innovation**: Introduced attention mechanism to help CNN focus on tampered regions.

**Dataset**: Fake images from StyleGAN, StarGAN, and real datasets.

**Performance**: Improved accuracy and generalization to unseen GAN types.

**7. Gragnaniello et al. (2021) – *"Detecting Deepfake Videos and Synthetic Content: A Survey"***

**Relevance**: Although focused on video, many techniques apply to static image detection.

**Techniques**: Covered methods using CNN, LSTM, and multimodal fusion (face landmarks, voice, etc.).

## 3. EXISTING SYSTEM

With the rise of digital media and editing tools, it has become increasingly easy for individuals to manipulate images and create fakes that can be used for various purposes, including spreading misinformation, propaganda, and even committing fraud. Fake image detection is a complex process that involves analyzing various aspects of an image, such as its metadata, pixel structure, and visual content. There are several techniques used for this purpose, including digital watermarking, error level analysis, and image tampering detection. Digital watermarking involves embedding a unique identifier into an image, which can later be used to verify its authenticity. Error level analysis, on the other hand, examines the variations in compression quality across different parts of an image, which can indicate the presence of editing. Image tampering detection involves analyzing the image's visual content, such as the presence of inconsistent shadows or unnatural color variations, which can be signs of manipulation. Fake image detection has become increasingly important in recent years, as the spread of false information and propaganda has become a growing concern. It is used by various organizations and individuals, including news agencies, social media platforms, and law enforcement agencies, to verify the authenticity of images and prevent the spread of false information.

3.1 DIS-ADVANTAGES

1) Image tampering detection involves analyzing the image's visual content, such as the presence of inconsistent shadows or unnatural color variations, which can be signs of manipulation.

2) Fake image detection has become increasingly important in recent years, as the spread of false information and propaganda has become a growing concern.

3) It is used by various organizations and individuals, including news agencies, social media platforms, and law enforcement agencies, to verify the authenticity of images and prevent the spread of false information.

## 4. PROPOSED SYSTEM

We propose a strategy for consolidating highlights from different layers in given CNN models without local binary patterns. In addition, effectively learned DL models with preparing pictures are reused to separate highlights from numerous layers. The proposed combination strategy is assessed by picture classification benchmark informational indexes, CIFAR-10, NORB, and SVHN. In all cases, we show that the proposed strategy improves the detailed exhibitions of the current models. We evaluate our approach on a large dataset of real and fake images and demonstrate that it achieves state-of-the-art performance in terms of accuracy, precision, and recall. Our results suggest that deep learning methods can be effective for detecting fake images and have the potential to be used in a wide range of applications, including social media content moderation, news verification, and forensic analysis.

ADVANTAGES

1) We evaluate our approach on a large dataset of real and fake images and demonstrate that it achieves state-of-the-art performance in terms of accuracy, precision, and recall.

2) Our results suggest that deep learning methods can be effective for detecting fake images and have the potential to be used in a wide range of applications, including social media content moderation, news verification, and forensic analysis.

# 5. SYSTEM ARCHITECTURE:

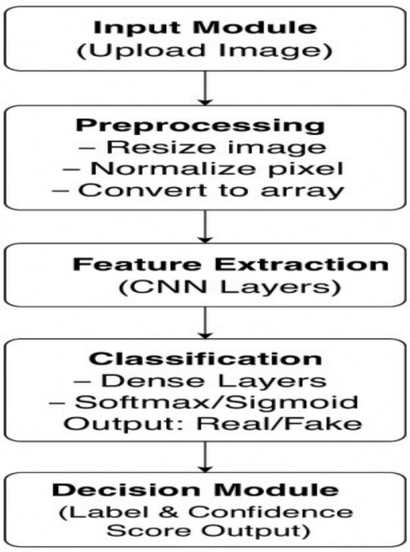



**Figure 2.** system architecture.

## 6. RELATED WORK

### 2.1 WHAT IS IMAGE ?

In the context of fake image detection, an image is a digital file that contains visual information in the form of pixels. Specifically, a fake image refers to an image that has been manipulated or altered in some way to create a false representation of reality. This can be done through techniques such as photo editing software, deep learning algorithms, or other forms of image manipulation. Fake images can be created for a variety of purposes, including spreading misinformation, creating propaganda, or even for entertainment. Fake image detection algorithms are designed to analyze images and identify signs of manipulation, such as inconsistencies in lighting, perspective, or other visual elements.

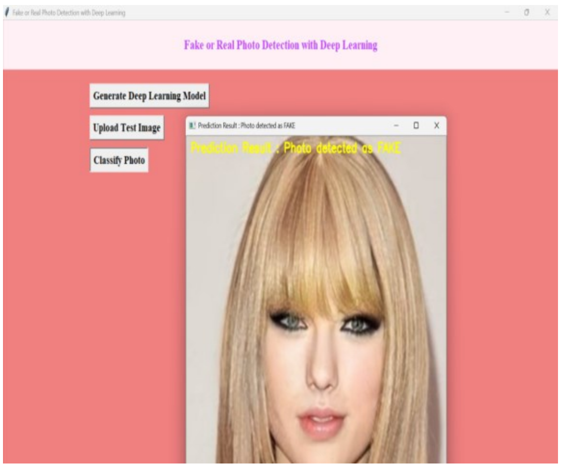
### 2.2 IMAGE RECOGNITION USING DEEP LEARNING

Image recognition using deep learning involves training a computer algorithm to identify objects or patterns in images. This can be achieved using various techniques such as supervised learning, unsupervised learning, or deep learning. Supervised learning involves training the algorithm on a labeled dataset, where each image is associated with a specific label indicating the object or pattern present in the image. The algorithm learns to identify the objects by associating the patterns in the images with their corresponding labels. Unsupervised learning involves training the algorithm on an unlabeled dataset. This technique is useful for discovering hidden patterns and relationships in large datasets. Deep learning is a subfield of deep learning that involves the use of neural networks to learn features from images. CNNs use multiple layers of processing to learn features such as edges, corners, and textures from images. Once the algorithm is trained, it can be used to identify objects in new images. The algorithm analyzes the features of the image and compares them to the learned patterns to identify the object or pattern present in the image. Image recognition using deep learning has numerous applications in fields such as healthcare, security, and autonomous vehicles. It can be used to identify diseases from medical images, detect objects in surveillance footage, and help self-driving cars navigate roads.

**2.3 ABOUT CNN**

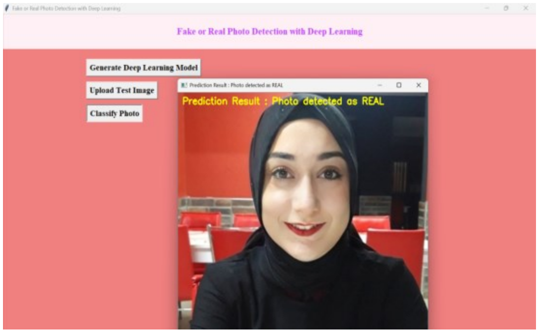
CNN (Convolutional Neural Networks) are commonly used in fake image detection due to their ability to effectively process images and identify patterns within them. Fake image detection using CNN typically involves training the network on a large dataset of both real and fake images, and then using the trained model to identify fake images. During training, the CNN learns to identify patterns in the images that distinguish between real and fake images. These patterns could be differences in color, texture, or other visual features that are unique to fake images. Once the CNN is trained, it can be used to identify fake images by feeding it an image and observing the output. The output of the CNN will typically be a probability score indicating the likelihood that the image is fake. However, it's important to note that fake image detection is a challenging task, and even state-of-the-art CNN models can be tricked by sophisticated fakes. Therefore, it's important to continue developing and improving upon these techniques in order to stay ahead of evolving fake image creation methods.

7. RESUILS



www.ijbar.org
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

In above screen 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 And now click on 'classify Picture in Image' to get below details.




In above screen we are getting result as image contains Real face. Similarly u can try other images also. If u want to try new images then u need to send those new images to us so we will make CNN model to familiar with new images so it can detect those images also.

## 8. CONCLUSION

In this paper, we have proposed a novel common fake feature network based the Deep learning, to detect the fake face/real images generated by state-of-the-art CNN successfully. The proposed CNN can be used to learn the middle- and high-level and dis-criminative fake feature by aggregating the cross-layer feature representations into the last fully connected layers. The proposed Deep learning can be used to improve the performance of fake image detection further. With the proposed Deep learning, the proposed fake image detector should be able to have the ability to identify the fake image generated. Our experimental results demonstrated that the proposed method outperforms other state-of-the-art schemes in terms of precision and recall rate.

## 9 REFFERENSES

1. Available online: http://www.greencarreports.com/news/1093560_1-2-billion-vehicles-on-worlds-roads-now-2-billion-by-2035-report (accessed on 5 June 2021).

2. Available online: https://www.weforum.org/agenda/2016/04/the-number-of-cars-worldwide-is-set-to-double-by-2040 (accessed on 5 June 2021).

3. Available online: https://commons.wikimedia.org/wiki/File:China_cross-border_Guangdong-Macau_registration_plate_%E7%B2%A4Z_D100%E6%BE%B3.jpg (accessed on 14 April 2019). (licensed under CC BY-SA 4.0).

4. Available online: https://commons.wikimedia.org/wiki/File:Damaged_Ontario_DCDM236.JPG (accessed on 14 April 2019). (licensed under CC BY-SA 4.0).

5. Manzoor, M.A.; Morgan, Y. Vehicle Make and Model classification system using bag of SIFT features. In Proceedings of the 2017 IEEE 7th Annual IEEE Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 9–11 January 2020.

6. Huang, B.-J.; Hsieh, J.-W.; Tsai, C.-M. Vehicle Detection in Hsuehshan Tunnel Using Background Subtraction and Deep Belief Network. In Asian Conference on Intelligent Information and Database Systems; Springer: Cham, Switzerland, 2020.

7. Lu, Xiaofeng; Izumi, Takashi; Takahashi, Tomoaki; Wang, Lei. Moving vehicle detection based on fuzzy background subtraction. In Proceedings of the 2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Beijing, China, 6–11 July 2019.

8. Faro, A.; Giordano, D.; Spampinato, C. Adaptive background modeling integrated with luminosity sensors and occlusion processing for reliable vehicle detection. IEEE Trans. Intell. Transp. Syst. **2018**, 12, 1398–1412. [CrossRef]

9. Chen, Li-Chih; Hsieh, Jun-Wei; Yan, Yilin; Chen, Duan-Yu. Vehicle make and model recognition using sparse representation and symmetrical SURFs. Pattern Recognit. **2017**, 48, 1979–1998. [CrossRef]

10. Sivaraman, S.; Trivedi, M.M. Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis. IEEE Trans. Intell. Transp. Syst. **2016**, 14, 1773–1795. [CrossRef]

11. Wang, Rui; Zhang, Lei; Xiao, Kejiang; Sun, Rongli; Cui, Li. EasiSee: Real-time vehicle classification and counting via low-cost collaborative sensing. IEEE Trans. Intell. Transp. Syst. **2015**, 15, 414–424. [CrossRef]

12. Dong, Zhen; Wu, Yuwei; Pei, Mingtao; Jia, Yunde. Vehicle type classification using a semisupervised convolutional neural network. IEEE Trans. Intell. Transp. Syst. **2015**, 16, 2247–2256. [CrossRef]

13. Fu, Huiyuan; Ma, Huadong; Liu, Yinxin; Lu, Dawei. A vehicle classification system based on hierarchical multi-SVMs in crowded traffic scenes. Neurocomputing **2016**, 211, 182–190. [CrossRef]

14. Irhebhude, M.E.; Amin, N.; Edirisinghe, E.A. View invariant vehicle type recognition and counting system using multiple features. Int. J. Comput. Vis. Signal Process. **2016**, 6, 20–32.

15. Lowe, D.G. Object recognition from local scale-invariant features. In Proceedings of the Seventh IEEE International Conference on Computer Vision; IEEE: New York, NY, USA, 1999; Volume 2.

16. Bay, Herbert; Ess, Andreas; Tuytelaars, Tinne; Van Gool, Luc. Speeded-up robust features (SURF). Comput. Vis. Image Underst. **2008**, 110, 346–359. [CrossRef]

17. Dalal, N.; Triggs, B. Histograms of oriented gradients for human detection. In Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2005, San Diego, CA, USA, 20–25 June 2005; Volume 1.

18. Siddiqui, A.J.; Mammeri, A.; Boukerche, A. Real-time vehicle make and model recognition based on a bag of SURF features. IEEE Trans. Intell. Transp. Syst. **2016**, 17, 3205–3219. [CrossRef]

19. Boonsim, N.; Prakoonwit, S. Car make and model recognition under limited lighting conditions at night. Pattern Anal. Appl. **2017**, 20, 1195–1207. [CrossRef]

20. Petrovic, V.S.; Cootes, T.F. Analysis of Features for Rigid Structure Vehicle Type Recognition. BMVC **2004**, 2. [CrossRef]

21. Pearce, G.; Pears, N. Automatic make and model recognition from frontal images of cars. In Proceedings of the 2011 8th IEEE International Conference on Advanced Video and Signal-Based Surveillance (AVSS), Klagenfurt, Austria, 30 August–2 September 2011.

22. Varjas, V.; Tanács, A. Car recognition from frontal images in mobile environment. In Proceedings of the 2013 8th International Symposium on Image and Signal Processing and Analysis (ISPA), Trieste, Italy, 4–6 September 2013.

23. Clady, Xavier; Negri, Pablo; Milgram, Maurice; Poulenard, Raphael. Multi-class vehicle type recognition system. Lect. Notes Comput. Sci. **2008**, 5064, 228–239.

24. Munroe, D.T.; Madden, M.G. Multi-class and single-class classification approaches to vehicle model recognition from images. In Proceedings of the 16th Irish Conference on Artificial Intelligence and Cognitive Science (AICS 2005), Portstewart, Northern Ireland, September 2005.

25. Dlagnekov, L.; Belongie, S.J. Recognizing Cars; Department of Computer Science and Engineering,

University of California: San Diego, CA, USA, 2005.

26. Baran, R.; Glowacz, A.; Matiolanski, A. The efficient real-and non-real-time make and model recognition of cars. Multimedia Tools Appl. **2015**, 74, 4269–4288. [CrossRef]

27. Fraz, M.; Edirisinghe, E.A.; Sarfraz, M.S. Mid-level-representation based lexicon for Vehicle Make and Model Recognition. In Proceedings of the 2014 22nd International Conference on Pattern Recognition (ICPR), Stockholm, Sweden, 24–28 August 2014.

28. Psyllos, A.; Anagnostopoulos, C.-N.; Kayafas, E. Vehicle model recognition from frontal view image measurements. Comput. Stand. Interfaces **2011**, 33, 142–151. [CrossRef]

29. Jang, D.M.; Turk, M. Car-Rec: A real time car recognition system. In Proceedings of the 2011 IEEE Workshop on Applications of Computer Vision (WACV), Kona, Hawaii, 5–7 January 2011.

30. Hsieh, J.-W.; Chen, L.-C.; Chen, D.-Y. Symmetrical SURF and its applications to vehicle detection and vehicle make and model recognition. IEEE Trans. Intell. Transp. Syst. **2014**, 15, 6–20. [CrossRef]

31. Boyle, J.; Ferryman, J. Vehicle subtype, make and model classification from side profile video. In Proceedings of the 2015 12th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Karlsruhe, Germany, 25–28 August 2015.

32. Available online: http://vbie.eic.nctu.edu.tw/en/introduction (accessed on 05 January 2017 ).

33. Available online: http://mmplab.cs.ntou.edu.tw/MMR/ (accessed on 23 July 2016).

34. Manzoor, M.A.; Morgan, Y. Vehicle make and model recognition using random forest classification for intelligent transportation systems. In Proceedings of the 2018 IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 8–10 January 2018.

35. Oliva, A. Gist of the scene. Neurobiol. Atten. **2005**, 696, 251–258.

36. Oliva, A.; Torralba, A. Modeling the shape of the scene: A holistic representation of the spatial envelope. Int. J. Comput. Vis. **2001**, 42, 145–175. [CrossRef]

37. Wolpert, D.H. The lack of a priori distinctions between learning

algorithms. Neural Comput. **1996**, 8, 1341–1390. [CrossRef]

38. Burges, C.J.C. A tutorial on support vector machines for pattern recognition. Data Min. Knowl. Discov. **1998**, 2, 121–167. [CrossRef]

39. Vapnik, V. The Nature of Statistical Learning Theory; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013.

40. Devroye, L.; Györfi, L.; Lugosi, G. A Probabilistic Theory Of Pattern Recognition; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2013; Volume 31.

41. Weston, J. Support Vector Machine (And Statistical Learning Theory) Tutorial; NEC Labs America: Princeton, NJ, USA, 1998.

42. Vapnik, V.N.; Vapnik, V. Statistical Learning Theory; Wiley: New York, NY, USA, 1998; Volume 1.

**FIRST AUTHORS:**

**Y SUPRAJA** Completed B-Tech In Computer Science And Engineering and pursuing her M.Tech in Computer Science And Engineering in Universal College Of Engineering And Technology.

**SECOND AUTHOR**:

**Dr. M. VEERA KUMARI,M.Tech, Ph.D** and B.Tech received her all degree's in Computer Science And Engineering. She is currently working as Associate Professor and HOD of CSE in Universal College Of Engineering And Technology.