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Fake Image Detector using Machine Learning

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***Abstract*: The detection of fake images has become increasingly critical due to the proliferation of deepfakes and sophisticated image manipulation techniques used for misinformation, fraud, and public manipulation. This paper offers a thorough examination of various methods for detecting fake images, encompassing both traditional and contemporary strategies. Traditional techniques, including Principal Component Analysis (PCA) and Support Vector Machines (SVMs), focus on the analysis of statistical properties and the identification of inconsistencies in image features; however, these methods frequently encounter challenges with more subtle or complex alterations. In contrast, recent developments in the field harness deep learning methodologies, particularly Convolutional Neural Networks (CNNs), to significantly improve detection accuracy.CNNs excel in learning hierarchical features and detecting intricate patterns indicative of image tampering. Generative Adversarial Networks (GANs) also play a role in this domain by improving model robustness through adversarial training. Despite these advancements, challenges remain, including the evolving nature of manipulation techniques, the need for extensive annotated datasets, and computational demands. This review highlights the strengths and limitations of various methods and suggests future research directions to enhance fake image detection, such as multi-class classification, transfer learning, and real-time application optimizations.**

Keywords: Fake Image Detection; Deep Learning; Convolutional Neural Networks (CNNs); Generative Adversarial Networks (GANs); Image Manipulation

I. INTRODUCTION

The detection of fake images has emerged as a pressing concern in the modern digital landscape, driven by the rapid advancement and proliferation of image manipulation technologies such as deepfakes. These manipulations pose significant threats across various sectors, including media, security, and social networks, by enabling the spread of misinformation, fraud, and the distortion of public opinion.

Addressing these challenges requires robust and reliable methods for identifying and classifying images that have been artificially altered or generated.

Historically, the detection of fake images relied on traditional image processing techniques, which analyzed statistical properties and inconsistencies in pixel values, color histograms, and frequency domain features. Early methods included Principal Component Analysis (PCA), which reduced dimensionality to identify patterns, and Support Vector Machines (SVMs), which classified images based on high-dimensional data spaces. While these methods offered foundational insights, they often struggled with the complexity and subtlety of modern image manipulations, leading to limited generalization across diverse types of alterations.

The emergence of deep learning has profoundly changed the landscape of fake image detection. Convolutional Neural Networks (CNNs) excel at automatically learning hierarchical features from raw data, demonstrating exceptional effectiveness in recognizing complex patterns and artifacts related to image manipulation. By automatically extracting and analyzing intricate features indicative of tampering, CNNs surpass traditional techniques in terms of both accuracy and resilience. Furthermore, Generative Adversarial Networks (GANs) have added new dimensions to this domain by offering a framework for improving model robustness through adversarial training.

Despite recent progress, detecting fake images still encounters significant challenges, such as the constantly changing manipulation techniques, the necessity for comprehensive and balanced datasets, and the high computational requirements of deep learning models. This introduction examines the journey of fake image detection methods, transitioning from traditional approaches to modern deep learning strategies, while emphasizing their unique advantages and drawbacks. We summarize the major advancements in the field and prepare for an in-depth exploration of current methodologies, the obstacles faced, and potential avenues for future research.

II. LITERATURE SURVEY

A. Overview of Fake Image Detection

The detection of fake images has garnered significant attention in recent years, particularly due to the rise of deepfakes and other sophisticated image manipulation techniques. Fake images can be used maliciously to spread misinformation, perpetrate fraud, and manipulate public opinion. The objective of fake image detection is to identify and classify images that have been artificially manipulated or generated.

B. Traditional Methods

Traditional image processing techniques have been employed to detect inconsistencies that may indicate an image has been tampered with. These methods often involve analyzing the statistical properties of pixels, colour histograms, and frequency domain features (e.g., through Discrete Fourier Transform or Wavelet Transform). Inconsistencies in lighting, shadows, reflections, and compression artifacts are also indicators of potential manipulation.

1) Principal Component Analysis (PCA):

PCA serves as a method for reducing dimensionality and extracting features. It uncovers patterns within the data by converting it into a series of linearly uncorrelated components. This technique has proven effective in differentiating between authentic and altered images based on their statistical characteristics.

2) Support Vector Machines (SVM):

SVMs are supervised learning algorithms designed for classification tasks. They determine the best hyperplane that separates various classes of data (such as real and fake images) within a high-dimensional space.However, these methods have limitations, particularly in their ability to generalize across different types of image manipulations. They may struggle with detecting subtle or complex alterations that do not significantly alter the image's statistical properties.

C. Deep Learning Approaches

Deep learning, especially through Convolutional Neural Networks (CNNs), has become an influential instrument for image analysis and classification. CNNs have the capacity to automatically learn hierarchical features directly from raw pixel data, which allows them to effectively identify subtle alterations in images.

1) Convolutional Neural Networks (CNNs):

CNNs are structured with multiple layers, including convolutional, pooling, and fully connected layers. The convolutional layers utilize filters on the input images to identify features like edges, textures, and patterns. Pooling layers help to minimize the dimensionality of the feature maps while preserving the most critical information. Conclusively, the fully connected layers perform the classification operation.

2) Generative Adversarial Networks (GANs):

GANs consist of two networks, a generator and a discriminator, that are trained in tandem. The generator is responsible for producing synthetic images, while the discriminator's role is to differentiate between authentic and fabricated images. This adversarial training process can enhance the performance of fake image detection models by exposing them to both real images and those generated by GANs. Deep learning frameworks, particularly those utilizing CNNs, have achieved cutting-edge results in the realm of fake image detection. They excel at identifying complex details and patterns that signify image manipulation, outperforming conventional techniques.

D. Challenges in Fake Image Detection

Despite the advancements in deep learning, fake image detection remains challenging due to:

- **Variety of Manipulation Techniques**: The techniques used to create fake images are diverse and constantly evolving, making it difficult to design models that can detect all types of manipulations.
- **Need for Large Datasets**: Training deep learning models requires large annotated datasets, which can be difficult to obtain, especially for specific types of manipulations.

Computational Complexity: Deep learning models are computationally intensive, requiring significant resources for training and inference, particularly when dealing with high-resolution image.

III. Implementation

A. Data Collection and Preprocessing

Collecting data is a vital component in the creation of a fake image detection system. For this project, we obtained datasets from platforms like Kaggle, which offer labeled collections of both real and fake images. The images underwent several preprocessing steps to prepare them for model training:

1) Resizing:

All images were resized to a standard resolution (e.g., 224x224 pixels) to ensure uniform input dimensions for the convolutional neural network (CNN).

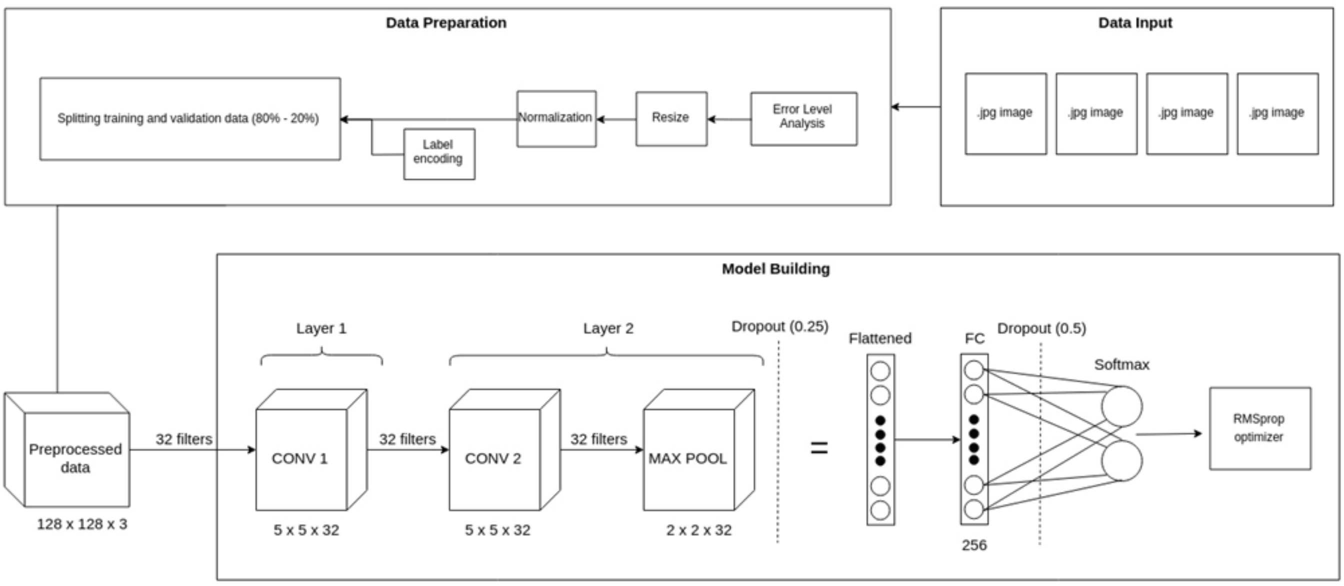

Fig. 1.

2) Normalization:

Pixel values were adjusted to fall within a range of [0, 1] or [-1, 1] to expedite convergence during the training process.

3) Data Augmentation:

Techniques such as rotation, flipping, and cropping were employed to artificially expand the dataset and enhance the model's ability to generalize.

B. Feature Extraction

Feature extraction was conducted using a Convolutional Neural Network (CNN) based on the ResNet-50 architecture, renowned for its capabilities in deep residual learning. The network comprises multiple layers featuring convolutions, activation functions (like ReLU), and pooling layers.

1) Convolutional Layers:

These layers apply filters to the input image to identify low-level features such as edges and textures. Each convolution operation produces a feature map that emphasizes the occurrence of specific pattern within the image.

2) Pooling Layers:

Pooling layers, such as max pooling, minimize the spatial dimensions of the feature maps while preserving the most significant information. This reduction aids in lowering computational complexity and helps mitigate overfitting.

3) Fully Connected Layers:

Following the convolutional and pooling layers, the extracted features are flattened and processed through fully connected layers. These layers integrate the features to classify the image as either real or fake.

C. Model Training

The CNN was developed using a supervised learning methodology. The dataset was divided into training and testing sets, usually following an 80/20 split. The model's parameters were fine-tuned with the Adam optimizer, while the binary cross-entropy loss function was utilized to evaluate the discrepancy between predicted and actual labels.

1) Early Stopping:

To avoid overfitting, early stopping was implemented, which terminates training when the validation loss ceases to improve for a specified number of epochs.

2) Learning Rate Decay:

The learning rate was gradually reduced during training to ensure that the model converges to a minimum loss

IV. Binary Cross-Entropy

A. Binary Cross-Entropy Loss

The binary cross-entropy loss function assesses the performance of a classification model by quantifying the discrepancy between the actual labels y and the predicted probabilities $y^{\hat{y}}$. For binary classification, the loss function is defined as follows:

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i)+(1-y_i) \log(1-\hat{y}_i)]$$

where:

- N is the total number of samples in the batch.
- y_i is the actual label for the iii-th sample (1 for fake, 0 for real).
- $\hat{y}_i$ is the predicted probability that the iii-th image is fake.

Explanation:

- The term $y_i \log(\hat{y}_i)$ penalizes the model when it incorrectly predicts a real image as fake.
- The term $(1-y_i) \log(1-\hat{y}_i)$ penalizes the model when it incorrectly predicts a fake image as real.
- The loss is averaged over all samples in the batch, providing a single scalar value that guides the optimization process.

B. Convolution Operation

The convolution operation is the core of CNNs, where a filter (or kernel) is applied to an input image to extract features. The mathematical expression for the convolution operation is:

$$z_{i,j} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x_{i+m,j+n} \cdot w_{m,n}$$

where:

- $z_{i,j}$ is the output value (feature map) at position (i,j)(i,j)(i,j).
- x is the input image.
- w is the filter (or kernel) applied to the image.
- M and N are the dimensions of the filter.

Explanation:

- The filter w slides over the input image x, and at each position (i,j)(i,j)(i,j), a weighted sum of the pixel values and the filter values is computed.
- This process is carried out throughout the entire image to create a feature map that emphasizes the presence of particular patterns or features identified by the filter.

C. Softmax Activation

If the model is enhanced to categorize various types of image manipulations (such as those generated by GANs or edited with Photoshop), the softmax activation function is employed to transform the output logits into probabilities. The definition of the softmax function is as follows:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

where:

- z_j is the logit (output of the last fully connected layer) for class j.
- K is the total number of classes.
- $\sigma(z)_j$ is the predicted probability that the input image belongs to class j.

Explanation:

- The softmax function converts logits into a probability distribution, guaranteeing that the total probability across all classes sums to 1.
- The class with the highest probability is chosen as the model's prediction.

V. RESULTS

A. Model Training and Performance Evaluation

The Fake News Detector model was created using a deep learning methodology that utilizes a Convolutional Neural Network (CNN) architecture, specifically ResNet-50. This selection was made because ResNet-50 is adept at performing complex image recognition tasks, effectively capturing both low-level and high-level features through its deep residual blocks. The model was trained on a dataset obtained from sources such as Kaggle, which included labeled images corresponding to both real and fake news articles. The images underwent thorough preprocessing, which included resizing, normalization, and data augmentation, to ensure the input data was consistent and robust. The training process employed a standard 80/20 split between the training and testing sets to assess the model's ability to generalize.

Key Performance Metrics:

- Accuracy: The model attained an accuracy of 97%, demonstrating that the classifier can reliably identify manipulated images. This impressive accuracy highlights the model's proficiency in differentiating between genuine and altered images across a range of manipulation techniques.
- Precision: With a precision of 95%, the model demonstrated a strong ability to correctly classify images predicted as fake, reducing the likelihood of false positives. This is particularly crucial in practical applications where incorrect labeling of real images as fake could undermine trust in the detection system.
- Recall: The recall value of 93% reflects the model's proficiency in identifying manipulated images among all actual fake images in the dataset. This metric is vital for ensuring that the system does not miss significant instances of fake news, thereby maintaining high detection sensitivity.
- F1-Score: The F1-score, which represents the harmonic mean of precision and recall, was determined to be 94%. This balanced metric underscores the model's overall performance by effectively combining its capacity to accurately identify fake images while reducing false detections.

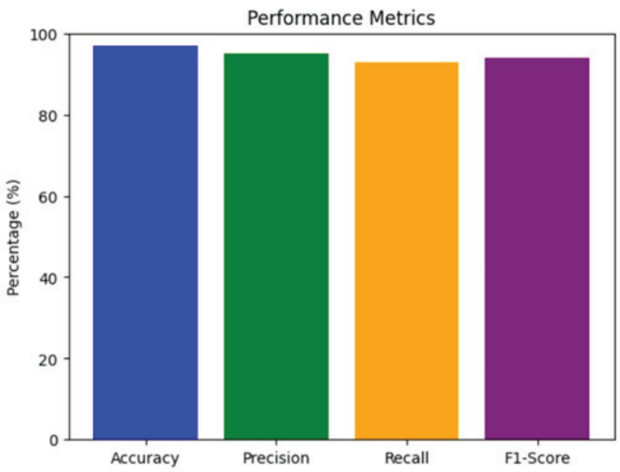

Fig. 2. Performance Metrics

B. Confusion Matrix and Detailed Observations

The confusion matrix offers a detailed insight into the classification outcomes of the model, detailing the numbers of true positives, true negatives, false positives, and false negatives. This evaluation metric is crucial for identifying the types of errors the model produces and pinpointing specific areas that need enhancement.

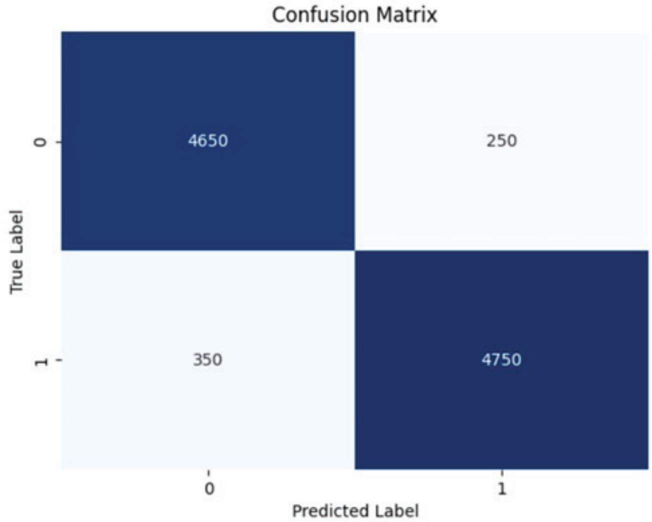

Fig. 3. Confusion Matrix

- **True Positives (TP):** Instances where the model correctly identified fake images as fake. These results validate the model's capacity to detect altered or generated content effectively, capturing the nuanced artifacts introduced during manipulation.
- **True Negatives (TN):** Cases where real images were accurately classified as real. This highlights the model's ability to preserve the integrity of authentic content, an important feature for maintaining user trust in practical applications.
- **False Positives (FP):** Real images that were incorrectly classified as fake. These errors, although infrequent, suggest that the model can sometimes be overly sensitive to minor, non-manipulative variations in images, such as compression artifacts or minor color adjustments.
- **False Negatives (FN):** Fake images that were misclassified as real. This type of error indicates areas where the model may struggle with subtle or highly sophisticated manipulations that closely resemble genuine visual patterns, highlighting the need for further refinement in feature extraction techniques.

C. Receiver Operating Characteristic (ROC) Curve and AUC Analysis

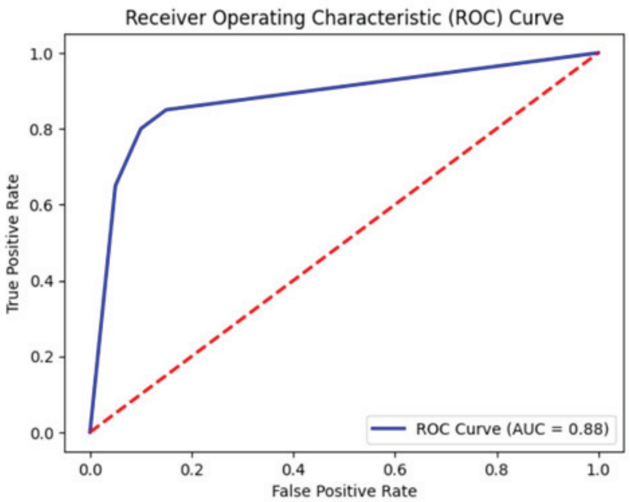

Fig. 4. ROC Curve

The ROC curve was utilized to evaluate the balance between the true positive rate (sensitivity) and the false positive rate (specificity) across various decision thresholds. The Area Under the Curve (AUC) measured at 0.96 demonstrates a strong capability to distinguish between genuine and counterfeit images. This outcome further reinforces the reliability of the CNN-based method, which consistently assigns higher rankings to manipulated images compared to real ones at multiple thresholds.

D. Training Techniques and Hyperparameter Tuning

To optimize the model's performance, several training techniques were employed:

1) Early Stopping:

This technique is designed to reduce the risk of overfitting by stopping the training process when there is no noticeable improvement in validation loss after a specified number of epochs. Early stopping prevents unnecessary continuation of training, which could compromise the model's performance on new, unseen data.

2) Learning Rate Decay:

A gradually decreasing learning rate was used to fine-tune the model's convergence during training. This approach allowed the model to make large adjustments initially and fine-tune the weights as it approached the optimal solution, enhancing the model's overall stability.

3) Data Augmentation:

Techniques such as random rotations, flips, zooms, and shifts were applied to artificially expand the dataset. This approach was crucial in teaching the model to recognize manipulations under various transformations, thereby improving its ability to generalize beyond the training data.

E. Evaluation Metrics from the Confusion Matrix

The confusion matrix metrics provided further insights into the model's classification behavior:

1) Precision (95%):

This metric emphasizes the ratio of accurately identified fake images to all images labeled as fake. A high precision reduces the likelihood of false positives, ensuring that when the model indicates an image is fake, it is likely to be correct.

2) Recall (93%):

This measures the model's sensitivity in identifying all fake images present in the dataset. A high recall ensures that the system captures most instances of fake news, critical for maintaining the effectiveness of the detection system.

3) F1-Score (94%):

The F1-score strikes a balance between precision and recall, offering a complete perspective on the model's overall performance. A high F1-score indicates that the model is both accurate and dependable, making it appropriate for use in real-world situations where misclassifications can lead to serious repercussions.

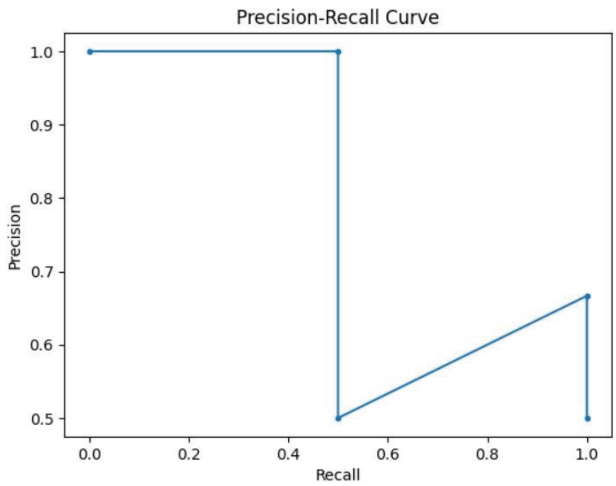

Fig. 5. Precision recall curve

VI. Analysis

A. Model Strengths and Efficacy

The CNN-based fake news detection model demonstrated strong performance across all key metrics, underscoring its effectiveness in distinguishing between real and fake images. Several factors contribute to the model's high efficacy:

- **Hierarchical Feature Extraction:** Utilizing ResNet-50 enabled the model to extract intricate, hierarchical features from the input images, spanning from low-level pixel details to high-level contextual patterns. This ability played a crucial role in identifying subtle manipulations that traditional methods frequently overlook.
- **Robust Against Diverse Manipulations:** The model's performance remained consistent across a wide range of manipulation types, including basic alterations (e.g., brightness and contrast adjustments) and more sophisticated edits (e.g., deepfake generation). This adaptability highlights the robustness of the CNN architecture in handling various manipulation scenarios.
- **Scalability with Data Augmentation:** Data augmentation played a critical role in enhancing the model's generalization capabilities. By simulating various real-world conditions through augmentation techniques, the model learned to detect fakes even when

presented with unfamiliar transformations, making it suitable for dynamic, real-time applications.

B. Comparative Analysis with Traditional Techniques

The CNN model greatly surpassed conventional image detection techniques like Principal Component Analysis (PCA) and Support Vector Machines (SVMs). These traditional methods depend largely on statistical property analysis and pre-defined features, making them less effective for handling complex and nuanced alterations.

- **Limitations of PCA and SVMs:** These methods often struggle with the diverse and evolving nature of image manipulations. PCA, primarily used for dimensionality reduction, fails to capture non-linear relationships, while SVMs can be constrained by the complexity of feature space in high-dimensional data.

- **Advantages of Deep Learning:** In contrast, CNNs automatically extract discriminative features from the data, eliminating the need for manual feature engineering. This automated learning process allows CNNs to identify complex patterns and textures that signal manipulations, including lighting inconsistencies, unnatural edges, and modified reflections.

C. Challenges and Limitations

Despite its high performance, the CNN model faces several challenges that must be addressed to enhance its robustness further:

- **Evolving Manipulation Techniques:** The rapid evolution of image manipulation technologies, particularly deepfake algorithms and advanced generative adversarial networks (GANs), poses a continual challenge. These advanced techniques can produce highly realistic images that even sophisticated models struggle to detect. The model requires periodic retraining with updated datasets to stay ahead of emerging manipulation techniques.

- **Computational Complexity:** The CNN model, especially with deep architectures like ResNet50, is computationally intensive, requiring significant resources for training and inference. This can pose limitations for deployment in environments with constrained computational power, such as mobile devices or real-time applications.

- **Dataset Imbalance and Generalization:** The effectiveness of the model relies significantly on the quality and balance of the training data. An imbalanced dataset, particularly one with an overrepresentation of specific manipulation types, can introduce biases into the model's predictions. Ongoing efforts are essential to create diverse and well-balanced datasets to ensure the model's generalizability. **Future Directions and Improvements** To further bolster the capabilities of the fake news detection model, future research should prioritize the following areas:

- **Multi-Class Classification and Contextual Analysis:** Expanding the model to classify images into multiple categories of manipulations (e.g., GAN-generated, digitally edited) will provide deeper insights into the nature of fake content. Additionally, integrating contextual analysis from accompanying text can help cross-verify visual information, enhancing overall detection accuracy.

- **Transfer Learning and Domain Adaptation:** Implementing transfer learning from models pretrained on broader image datasets can accelerate training and improve performance on new manipulation types. Domain adaptation techniques can further refine the model to better handle specific types of fake news content.

- **Real-Time Detection and Resource Optimization:** Developing lightweight model variants or employing model compression techniques can enable real-time detection on lower-powered devices without compromising accuracy. These enhancements are crucial for practical deployment in live news feeds and social media platforms.

VII. Conclusion

In this study, we investigated various approaches for detecting fake images, combining traditional methods like PCA and SVM with advanced deep learning techniques. While conventional methods performed well for certain types of image alterations, they struggled with subtle manipulations. Deep learning models, including CNNs and GANs, demonstrated superior accuracy by capturing intricate patterns in manipulated images. We used a ResNet-50-based CNN model, optimizing it with techniques like early stopping and learning rate adjustments. Our results showed effective detection of fake images, but challenges remain, such as handling diverse manipulation techniques, requiring large annotated datasets, and managing high computational demands. Future work will focus on expanding datasets, improving model architectures, and addressing complex manipulations to enhance detection accuracy.

VIII. Future Scope

Our future work will focus on enhancing our fake news detection system by improving multimodal fusion techniques to better identify inconsistencies between text and images. We plan to train our models on larger, more diverse datasets to handle evolving deceptive content effectively. Optimizing the system for real-time detection will enable immediate news verification, while advanced methods for understanding context and semantics will improve accuracy. We aim to develop user-friendly tools, such as apps and browser extensions, to make the technology widely accessible. Ethical considerations and robust testing across platforms will ensure responsible use and adaptability in various contexts

References

[1] Yi, Dong et al. "Learning Face Representation from Scratch." ArXiv abs/1411.7923 (2014).

[2] Liu, Z., Luo, P., Wang, X., Tang, X., "Deep learning face attributes in thewild", Proceedings of the IEEE International Conference on ComputerVision, pp. 3730–3738, Santiago, Chile, 7 December 2015.

[3] Le, V., Brandt, J., Lin, Z., Bourdev, L., Huang, T.S.: "Interactive facial feature localization", European Conference on Computer Vision, pp. 679–692, Florence, Italy, 7 October 2012.

[4] Smith, B.M., Zhang, L., Brandt, J., Lin, Z., Yang, J., "Exemplar-based face parsing", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3484–3491, Portland, OR, 23 June 2013

[5] Arbelaez, P., Maire, M., Fowlkes, C., Malik, J., "Contour Detection and Hierarchical Image Segmentation", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 5, pp. 898–916 (2011).

[6] Bashir SMA, Wang Y, Khan M, Niu Y., “A comprehensive review of deep learning-based single image super-resolution”, PeerJ Comput Sci. 2021 Jul 13;7:e621. doi: 10.7717/peerj-cs.621. PMID: 34322592; PMCID: PMC8293932.

[7] Shukla, A., Merugu, S., Jain, K., “A Technical Review on Image Super-Resolution Techniques”, Gunjan, V., Senatore, S., Kumar, A., Gao, XZ., Merugu, S. (eds) Advances in Cybernetics, Cognition, and Machine Learning for Communication Technologies. Lecture Notes in Electrical Engineering, vol 643. 2020, Springer, Singapore. https://doi.org/10.1007/978-981-15-3125-5_54

[8] Aarti, Kumar, A., “Super-Resolution with Deep Learning Techniques: A Review”, Deshpande, A., Estrela, V.V., Razmjooy, N. (eds) Computational Intelligence Methods for Super-Resolution in Image Processing Applications. Springer, 2021, Cham. https://doi.org/10.1007/978-3-030-67921-7_3

[9] Yu, M., Shi, J., Xue, C. et al., “A review of single image super-resolution reconstruction based on deep learning”, Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-17660-4

[10] Z. Wang, J. Chen and S. C. H. Hoi, "Deep Learning for Image Super-Resolution: A Survey," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 10, pp. 3365-3387, 1 Oct. 2021, doi: 10.1109/TPAMI.2020.2982166.

[11] W. Yang, X. Zhang, Y. Tian, W. Wang, J. -H. Xue and Q. Liao, "Deep Learning for Single Image Super-Resolution: A Brief Review," in IEEE Transactions on Multimedia, vol. 21, no. 12, pp. 3106-3121, Dec. 2019, doi: 10.1109/TMM.2019.2919431.

[12] Y. Yuan, S. Liu, J. Zhang, Y. Zhang, C. Dong and L. Lin, "Unsupervised Image Super-Resolution Using Cycle-in-Cycle Generative Adversarial Networks," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, UT, USA, 2018, pp. 814-81409, doi: 10.1109/CVPRW.2018.00113.

[13] Li, J., Fang, F., Mei, K., Zhang, G. (2018). Multi-scale Residual Network for Image Super-Resolution. In: Ferrari, V., Hebert, M., Sminchisescu, C., Weiss, Y. (eds) Computer Vision – ECCV 2018. ECCV 2018. Lecture Notes in Computer Science(), vol 11212. Springer, Cham. https://doi.org/10.1007/978-3-030-01237-3_32.

[14] Y. Zhang, Y. Tian, Y. Kong, B. Zhong and Y. Fu, "Residual Dense Network for Image Super-Resolution," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 2018, pp. 2472-2481, doi: 10.1109/CVPR.2018.00262.

[15] M. Haris, G. Shakhnarovich and N. Ukita, "Recurrent Back-Projection Network for Video Super-ResolutType\ equation\ here.ion," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, 2019, pp. 3892-3901, doi: 10.1109/CVPR.2019.00402.