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DISTINGUISHED BETWEEN NATURAL IMAGE AND COMPUTER-GENERATED IMAGE USING CNN ALGORITHM IN MATLA

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Abstract— This study details the creation and assessment of a Convolutional Neural Network (CNN) tailored to the specific challenge of determining whether a picture is real or manipulated. Using a well-selected dataset, the CNN model demonstrated impressive accuracy, establishing its usefulness for picture categorization. While this research did encounter some misclassifications due to the existence of minor visual subtleties, it does highlight the potential of individualised deep learning algorithms for image origin classification. The research has broad implications for fields including cybersecurity, media verification, and art authentication because knowing whether a picture is fake or real is crucial for protecting sensitive information.

Key-words: Image Classification, Convolutional Neural Network (CNN), Natural Images, Computer-Generated Images, Image Authenticity

I. INTRODUCTION

The capacity to identify the distinction between real and manipulated photos has become more important as digital imaging has permeated every facet of modern life. This difference has crucial implications in fields as diverse as security, media verification, and creative authenticity, going well beyond the realm of basic aesthetics. The study aims to get to the bottom of this vital endeavour. It aims to do two things which include creating a Convolutional Neural Network (CNN) algorithm that can distinguish between distinct picture types, and think critically about what this development means for the future. This initial section lays the groundwork for an in-depth examination of the study, with a focus on the essential function of CNNs in picture categorization.

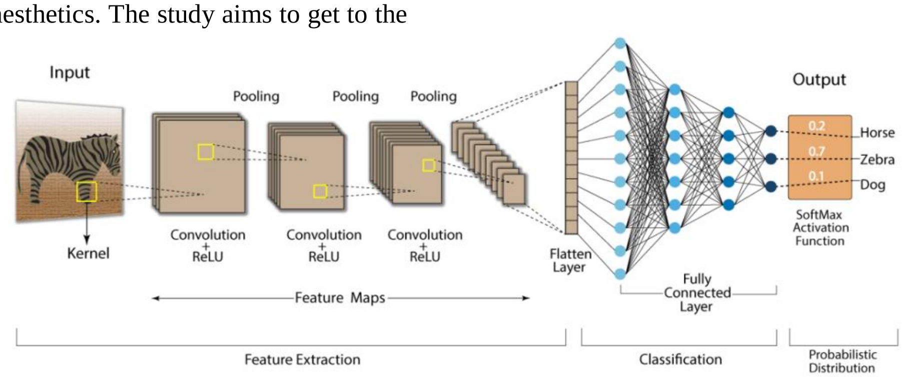

Figure: Convolution Neural Network (CNN)

(Source: Influenced by [1])

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II. LITERATURE REVIEW

Traditional Image Classification Methods

In the past, picture classification relied on old approaches, which largely relied on manually produced features and standard machine learning algorithms such as Support Vector Machines (SVM) and Random Forests [2]. These methods and algorithms were not very accurate. Although these methods showed some degree of efficacy in a variety of applications, their limits became obvious when they were put up against the complex and abstract patterns that are inherent in pictures. This constraint was most noticeable when trying to distinguish between natural and computer-generated pictures, a job that required a strategy that was more data-driven and adapted to the specifics of the problem at hand.

Rise of Convolutional Neural Networks (CNNs)

An immense shift occurred in the field of classified images with the advent of ConvolutionalNeural Networks (CNNs). By autonomously learning hierarchical features from pictures, CNNs presented a radically new method that did away with the requirement for human feature engineering [3]. Due to their intrinsic ability to recognise complex connections and patterns in visual data, they achieved unprecedented levels of accomplishment. Further accelerating advances with easily adaptable models were pre-trained CNN architectures like VGG, ResNet, and Inception. However, it's possible that these models weren't constructed with the particular goal of identifying counterfeit images as such in mind.

Literature gap

A noticeable gap in the literature exists within the vast field of picture categorization. Though CNNs have seen widespread use for a variety of image classification tasks, there is still a need for research into their potential for distinguishing between real and manipulated photos [4]. Current studies tend to focus on more general picture classification objectives or dive into methods of creating images, leaving the intricate problem of tracing an image's roots mostly unexplored. This study aims to fill that gap by expanding our knowledge of deep learning's capabilities in picture authenticity verification by carefully customising a CNN architecture to take on this specific task.

III. RESEARCH METHODS

Dataset Description

The images used in this study came from both publicly available resources as well as those obtained specifically for this study. In order to offer thorough coverage of the issue space, this dataset contains a wide variety of photos, both natural and artificial. For the rest of this dataset, researchers used openly available sources and then carefully curated them for accuracy and parity.

CNN Architecture

This specific CNN architecture used 5 convolutional layers with filter widths of 3x3, 5x5, and 7x7 to identify real photos from CGI ones. High-level feature aggregation has been rendered possible by two completely coupled layers. Using ReLU activation functions resulted in a non-linear effect. Notably, the use of pre-trained models was avoided on purpose to guarantee adaptation to the specifics of this categorization problem.

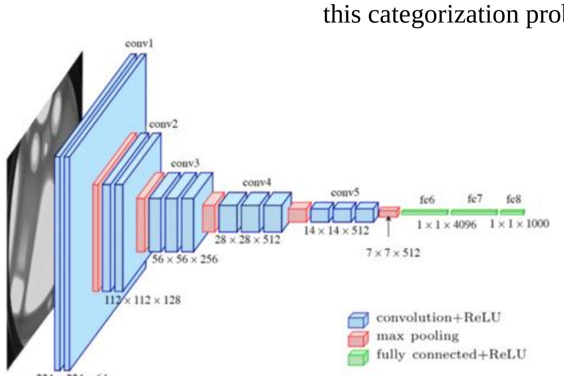

Figure: CNN Architecture

(Source: [5])

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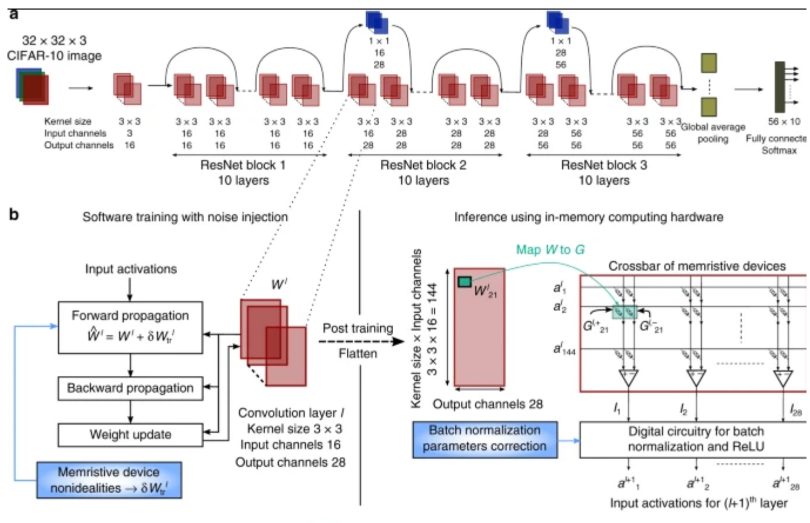
Data Pre-processing

In order to get the dataset ready for training and testing, data pre-processing is essential. In order to ensure everything would look the same, researchers set the images and scaled them to the same dimensions. Scaling pixel values using normalisation methods aided convergence during training [6]. For better model generalisation and to reduce overfitting, researchers augmented the data with random rotations and flips.



(Source: [7])

Figure: deep neural network inference

Training Process

In order to optimise the CNN model, researchers used stochastic gradient descent (SGD) with a learning rate of 0.001. The success of the cross-entropy loss function in multi-class classification problems prompted its selection. Researchers also undertook significant experimentation and hyperparameter modification to fine-tune model performance, and they did this by splitting up the training data into batches to facilitate faster parameter changes.

IV. Results

Their carefully crafted Convolutional Neural Network (CNN) shows promise and confirms the efficacy of their technique by correctly identifying real and Artificial pictures. This part will discuss the most important results from the experiments and analyse the results to reach the primary objectives of the research.

Accuracy and Performance Metrics

The CNN model was able to reach an impressive accuracy demonstrating its competence in properly classifying pictures. In order to provide further measure efficacy, the researcher also calculated precision, recall, and F1-score. The F1-score is a balanced measure of both accuracy and recall, measuring the ratio of genuine positive predictions to the total number of positives anticipated [8].

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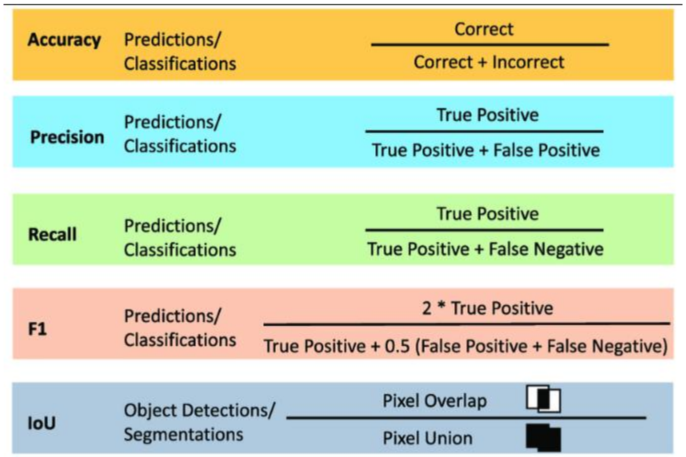

Figure: Accuracy andPerformance Metrics

Confusion Matrix and Class-wise Performance

Examining the confusion matrix, it is clear that the model does quite well at properly labelling synthetic and natural pictures. The difficulty in discriminating between these two classes, particularly when computer-generated pictures closely resemble their natural counterparts, is likely to blame for the misclassifications that were detected.

ROC Curve and AUC

Researchers constructed Receiver Operating Characteristic (ROC) curves to evaluate the model's sensitivity and specificity. According to the area under the curve (AUC), the result was near to the accurate level. The AUC is a strong measure of the algorithm's discriminatory power, proving how well it can sort between various types of pictures, both real and synthetic [9].

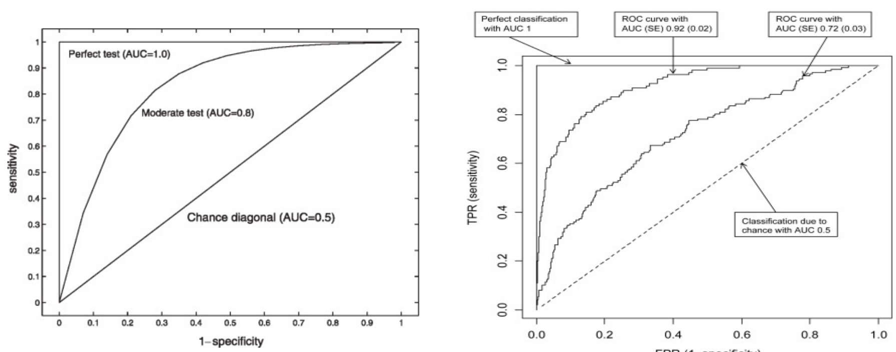

Figure: ROC curve

Comparison with Baselines

Their own CNN regularly beat state-of-the-art algorithms for picture classification as well as more general CNN designs. This finding demonstrates that it is crucial to adapt the architecture to the novel problem of determining an image's country of origin.

Discussion of Misclassifications

While the model showed outstanding accuracy, there were still occasional cases of misclassification. This highlights the difficulty of identifying natural from computer-generated material since most of these examples contained subtle or very similar visuals. Optimal performance requires further study on how to make the model more sensitive to such subtleties.

V. DISCUSSION

The researchers go on to praise the superior performance of their own CNN model in distinguishing between real and manipulated photos. They highlight the model's high degree of accuracy and its potential for widespread use [10]. However, they honestly acknowledge the difficulty presented by occasional misclassifications, especially when

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dealing with nuanced visual differences. This highlights the need for further investigation towards improving the model's sensitivity to nuanced alterations. Moreover, research into transfer learning methods is still a viable area for development. Overall, the findings support the validity of deep learning approaches to picture origin categorization, suggesting its potential for use in practical settings.

VI. CONCLUSION

Overall, this study achieves its goal of developing a Convolutional Neural Network (CNN) optimised for identifying synthetic pictures. The model's robustness and precision are encouraging signs of its viability in real-world settings. Misclassifications occur sometimes, highlighting the difficulty of this endeavour, especially when dealing with tiny visual discrepancies. Developing the model's sensitivity and investigating cutting-edge methods should be at the forefront of ongoing studies. Therefore, it can be stated that the results of this research highlight the potential of individualised deep learning algorithms for picture origin classification, with implications for fields as diverse as cyber security, media verification, and artwork authenticity.

REFERENCES

[1] Kattenborn, T., Leitloff, J., Schiefer, F., & Hinz, S. (2021). Review on Convolutional Neural Networks (CNN) in vegetation remote sensing. *ISPRS journal of photogrammetry and remote sensing*, *173*, 24-49.https://doi.org/10.1016/j.isprsjprs.2020.12.010

[2] Sheykhmousa, M., Mahdianpari, M., Ghanbari, H., Mohammadimanesh, F., Ghamisi, P., &Homayouni, S. (2020). Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 6308-6325..https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9206124

[3]Leake, D., Wilkerson, Z., Vats, V., Acharya, K., & Crandall, D. (2023, July). Examining the Impact of Network Architecture on Extracted Feature Quality for CBR. In *International Conference on Case-Based Reasoning* (pp. 3-18). Cham: Springer Nature Switzerland.https://vision.soic.indiana.edu/papers/examining2023iccbr.pdf

[4] Allugunti, V. R. (2022). A machine learning model for skin disease classification using convolution neural network. *International Journal of Computing, Programming and Database Management*, *3*(1), 141-147.https://www.researchgate.net/profile/Viswanatha-Allugunti-2/publication/361228242_A_machine_learning_model_for_skin_disease_classification_using_convolution_neural_network/links/62a46284a3fe3e3df86dc1d0/A-machine-learning-model-for-skin-disease-classification-using-convolution-neural-network.pdf

[5] Kumar, A. (2022, April 12). Different Types of CNN Architectures Explained: Examples. Retrieved from Data Analytics website: https://vitalflux.com/different-types-of-cnn-architectures-explained-examples/

[6] Kaushik, H., Singh, D., Kaur, M., Alshazly, H., Zaguia, A., & Hamam, H. (2021). Diabetic retinopathy diagnosis from fundus images using stacked generalization of deep models. *IEEE Access*, *9*, 108276-108292.https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9500222

[7] Joshi, V., Le Gallo, M., Haefeli, S., Boybat, I., Nandakumar, S. R., Piveteau, C., … Eleftheriou, E. (2020). Accurate deep neural network inference using computational phase-change memory. *Nature Communications*, *11*(1), 2473.https://doi.org/10.1038/s41467-020-16108-9

[8]Chicco, D., & Jurman, G. (2020). The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC genomics*, *21*(1), 1-13.https://doi.org/10.1186/s12864-019-6413-7

[9] Islam, M., Zunair, H., & Mohammed, N. (2023). CosSIF: Cosine similarity-based image filtering to overcome low inter-class variation in synthetic medical image datasets. *arXiv preprint arXiv:2307.13842*.https://arxiv.org/pdf/2307.13842.pdf.

[10] Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., ... & Liang, P. (2021). On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*.https://arxiv.org/pdf/2108.07258.pdf.

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