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INVESTIGATING DEEP LEARNING MODELS FOR NFT CLASSIFICATION: A REVIEW

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Abstract: Present research work is focused on NFT image classification using deep learning techniques. The classification task is extended by incorporating noise removal techniques in addition to image compression before employing the CNN model. After collecting and splitting the dataset, the images undergo both compression and noise removal processes to enhance their visual quality and reduce unwanted artifacts. The preprocessed images are then fed into a CNN model for training and evaluation. This approach aims to improve the model's ability to discern features in images by minimizing the impact of noise. The evaluation phase involves assessing the model's performance on the test set to determine its effectiveness in classifying NFT images after both compression and noise removal.
Keywords: NFT Classification, CNN, Noise removal and Image compression.

[1] Introduction

1.1 NFT Classification using Deep learning

Non-fungible tokens (NFTs) and their associated images have garnered substantial attention in recent years, fueled by their unique representation of ownership and authenticity in the digital realm. NFTs, often built on blockchain technology, provide a way to tokenize digital assets, including images, enabling creators to assign ownership and provenance to their works. In the context of NFTs, images play a crucial role as the visual representation of the digital asset. However, as the NFT ecosystem expands, the need for efficient and accurate NFT image classification becomes increasingly apparent. Deep learning, particularly convolutional neural networks (CNNs), has emerged as a powerful tool for image classification tasks, making it well-suited for the challenges posed by NFT image classification. One of the primary goals in this domain is to develop models capable of accurately categorizing and classifying NFT images into distinct groups or themes. This process involves training deep learning models on labeled datasets, where images are associated with specific NFT categories, genres, or attributes. The deep learning model learns intricate patterns, features, and representations from the training data, allowing it to generalize and make predictions on unseen NFT images. Image preprocessing steps, such as compression and noise removal, may be applied to enhance the model's ability to discern relevant information. The integration of transfer learning, where pre-trained models like ResNet or VGG16 are fine-tuned for NFT classification, can further improve efficiency and accuracy. However, the deployment of deep learning models for NFT image classification is not without its challenges. Issues related to image space consumption, time consumption, and achieving high accuracy must be carefully addressed. Balancing the computational demands of sophisticated models with the need for real-time or near-real-time processing is crucial for practical implementation. Intersection of NFTs and deep learning presents a dynamic landscape where technology converges with digital ownership and creativity. Deep learning models, especially those tailored for image classification, offer a promising avenue for efficiently categorizing NFT images, facilitating the growth and maturation of the NFT ecosystem.

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1.2 Role of image compression in preprocessing

The need for image compression before employing deep learning techniques is a multifaceted consideration that encompasses various aspects of computational efficiency, resource utilization, and model performance. Image compression plays a crucial role in optimizing the input data for deep learning models, and its significance can be understood through several key perspectives. Firstly, deep learning models often require substantial computational resources, and the size of the input data directly influences the training and inference times. Large, uncompressed images can be computationally expensive to process, requiring extensive memory and computational power. Image compression helps mitigate this challenge by reducing the file size while retaining essential features, thereby making the data more manageable and facilitating faster training and inference. Secondly, image compression contributes to the efficient use of storage space, an essential consideration in scenarios where vast datasets are involved. Storing and processing large volumes of uncompressed images can lead to significant resource overhead. By compressing images, the storage requirements are minimized, making it more feasible to handle and manipulate extensive datasets without undue strain on storage infrastructure. Moreover, image compression can be particularly advantageous when working with limited bandwidth or deploying models in real-time applications. For example, in scenarios where deep learning models need to process images in real-time, such as in autonomous vehicles or live video analysis, compressed images reduce the data transfer load and accelerate the overall processing speed. From a model performance perspective, image compression can enhance the generalization ability of deep learning models. Compression techniques often involve removing redundant information and noise from images, helping the model focus on the essential features for classification or regression tasks. This preprocessing step can contribute to improved model efficiency, generalization to unseen data, and, in some cases, resistance to overfitting. The integration of image compression before applying deep learning models is driven by the imperative to enhance computational efficiency, optimize storage, and improve model generalization. This preprocessing step is a practical solution to address the challenges associated with the size and complexity of image data, ensuring that deep learning models can be deployed effectively across various applications and industries.

1.3 Role of noise filtering in image preprocessing

Noise filtering in image preprocessing plays a pivotal role in enhancing the accuracy and robustness of deep learning models. Noise, in the context of images, refers to unwanted or irrelevant information that can be introduced during the image acquisition process or due to various environmental factors. By incorporating noise filtering techniques as part of the preprocessing pipeline before feeding images into deep learning models, several key advantages are realized. Firstly, noise filtering contributes to the improvement of image quality by reducing or eliminating undesirable artifacts. In many real-world scenarios, images captured by cameras or other sensors may be subject to interference such as random variations, blurring, or distortions. Noise filtering techniques, such as median filtering or Gaussian smoothing, effectively suppress these undesired elements, resulting in cleaner and more representative input data for the deep learning model. Secondly, the removal of noise aids in focusing the deep learning model on relevant features during the training process. Noise can introduce unnecessary variations that the model may mistakenly learn as patterns, leading to overfitting and reduced generalization performance on unseen data. By applying noise filtering as a preprocessing step, the model is exposed to more meaningful and representative features, improving its ability to discern essential patterns and characteristics in the images. Moreover, noise filtering contributes to increased model interpretability. Cleaned and preprocessed images allow for a more accurate understanding of the visual information presented to the model. This, in turn, assists in the interpretation of

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the model's decisions and facilitates better diagnostic analysis when the model is applied in fields such as medical imaging or quality control. In applications where high accuracy is crucial, such as medical image diagnosis or autonomous vehicles, noise filtering becomes imperative. It helps mitigate the adverse effects of noise on the model's decision-making process, resulting in more reliable and accurate predictions. Role of noise filtering in image preprocessing before deep learning is fundamental to optimizing model performance. By eliminating unwanted artifacts and enhancing image quality, noise filtering ensures that the deep learning model is provided with clean and informative input data, leading to improved accuracy, robustness, and interpretability in various applications.

1.2 Role of Deep learning models in NFT classification

Deep learning models, including Convolutional Neural Networks (CNNs) and Residual Networks (ResNets), play a pivotal role in the classification of Non-Fungible Token (NFT) images, where intricate visual details and diverse artistic styles necessitate advanced computational approaches. Convolutional Neural Networks (CNNs) are particularly well-suited for image classification tasks like those encountered in NFT platforms. Their hierarchical structure allows them to automatically learn and extract features from images, capturing local patterns, edges, and textures. CNNs are adept at recognizing spatial hierarchies within images, which is crucial in categorizing NFTs based on their unique visual characteristics. The translation invariance property of CNNs ensures that they can identify patterns regardless of their exact position in the image, making them robust to variations in composition and layout. Residual Networks (ResNets) address challenges associated with training very deep neural networks, a common requirement in NFT image classification tasks. The introduction of skip connections enables ResNets to effectively capture intricate features and details in NFT images without succumbing to the vanishing gradient problem. The enhanced gradient flow through skip connections facilitates the training of deep networks, allowing ResNets to learn and generalize from a diverse range of NFT images. Both CNNs and ResNets contribute significantly to the accuracy and efficiency of NFT image classification models. CNNs excel in their ability to automatically extract relevant features, while ResNets provide a solution to the degradation problem encountered in deep networks. The choice between these models depends on factors such as the complexity of the NFT dataset, the diversity of visual elements, and the depth of the neural network required for optimal classification performance.

In the context of NFT image classification, where the goal is to categorize digital assets based on their visual content, the utilization of CNNs and ResNets showcases the synergy between advanced deep learning architectures and the intricacies of digital art. These models not only provide accurate classifications but also offer interpretability, allowing users to understand the basis of classification decisions and enhancing the overall utility of NFT platforms.

There are different NFT projects that are holding NFT of particular pattern there remains some similarity in same class of NFT. For example NFT of 4 different classes are shown below:

Fig 1 NFT categories of 9NFTMANIA NFT

[2] Literature review

Gupta, M et al did work on. NFT Culture and presented a proposal for new era [1]. M. Gupta also reviewed the relationship between blockchain and NFT with world famous nft market places [2]. R. Gupta considered the role of liquidity pool in stabilizing value of token [3] whereas D. Gupta et al. [4] focused on investigating role of blockchain in building greetings valuable by making use of Thank you, Good morning NFT. PI network revolution and related NFT were discussed by R. Issalh [5]. A. Duggal did research work to present the significance of NFT avtaars in metaverse and did case study over it [6]. M. Gupta [7] did financial research to make appeal that there should be no speculation in Crypto market during NFT trades. A. Singla [8] discussed the impact of Bitcoin Halving on the Crypto Market. I. Gupta and P. Jain [9] did research on expected impact of decentralization using blockchain based technologies. D. Gupta and S. Gupta [10] explored world famous NFT Scripts. M. Gupta [11] wrote paper to present the integration of IoT and Blockchain for user Authentication. Parul [12] considered optimistic approach to create and sell antique pieces and their NFT.

[3] Problem statement

In the realm of NFT classification using deep learning models, several key challenges emerge, encompassing issues related to image space consumption, time consumption, and accuracy. These challenges reflect the intricate balance between computational efficiency and model performance. One significant concern revolves around image space consumption, particularly as it relates to the storage and transmission of NFT images. Deep learning models, especially those with a high level of complexity such as convolutional neural networks (CNNs) or integrated architectures like ResNet, demand substantial memory resources. The storage requirements for large-scale datasets of high-resolution NFT images can become a limiting factor, posing challenges for platforms and systems with constrained storage capacities. Moreover, the increased size of the model may lead to longer training times, exacerbating the overall computational burden. Time consumption constitutes another critical challenge in the deployment of deep learning models for NFT classification.

[4] NFT image classification using CNN model

The current study is centered on the classification of NFT images utilizing deep learning methodologies. Classification duty is expanded by integrating noise reduction strategies with picture compression prior to

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using the CNN model. Upon gathering and dividing the dataset, the photos undergo compression and noise reduction procedures to improve their visual quality and minimize undesired artifacts. The preprocessed photos are then inputted into a Convolutional Neural Network (CNN) model, similar to the initial scenario, for the purposes of training and assessment. The objective of this strategy is to enhance the model's capacity to identify features in pictures by reducing the influence of noise. The assessment step entails analyzing the model's performance on the test set to ascertain its efficacy in categorizing NFT pictures after both compression and noise removal.

Review of Algorithm for NFT image classification

Classifying NFT images using a Convolutional Neural Network (CNN) after image compression and noise removal involves additional steps compared to the previous algorithm. Below is an extended outline that includes the steps or noise removal.

1. Data Preparation:
   - Collect a dataset of NFT images with corresponding labels.
   - Split the dataset into training, validation, and testing sets.

2. Image Compression:
   - Apply the desired image compression technique to reduce the file size of the images.
   - Ensure that the compression does not significantly compromise the visual quality for effective classification.

3. Noise Removal:
   - Apply a noise removal technique to enhance the image quality. Common methods include:
     - Median filtering
     - Gaussian smoothing
     - Denoising autoencoders

4. Data Augmentation (Optional):
   - Augment the training dataset with techniques such as rotation, flipping, and zooming. This helps the model generalize better.

5. Preprocessing:
   - Normalize pixel values to a range suitable for the neural network (e.g., [0, 1] or [-1, 1]).
   - Resize the images to a consistent input size required by the CNN model.

6. CNN Model Architecture:
   - Define a CNN model suitable for image classification. You can use popular architectures like VGG, ResNet, or design a custom architecture based on your needs.
   - The input layer should match the size of the preprocessed images, and the output layer should have neurons corresponding to the number of classes.

7. Compile the Model:

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- Choose a loss function (e.g., categorical cross-entropy for multi-class classification) and an optimizer (e.g., Adam).
- Compile the model with these choices and any relevant metrics.

8. Training:
- Train the CNN model on the preprocessed, compressed, and noise-removed images using the training dataset.
- Utilize the validation set to monitor model performance and prevent overfitting.

9. Evaluation:
- Evaluate the model on the test set to assess its generalization performance.
- Analyze metrics such as accuracy, precision, recall, and F1 score.

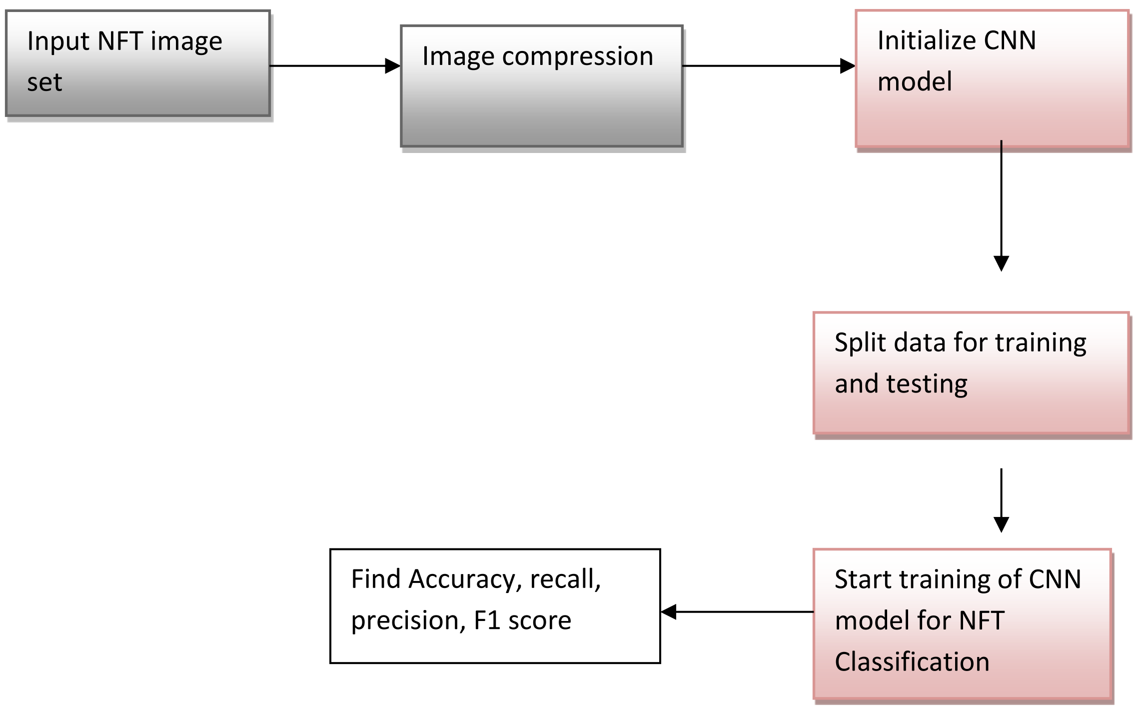

Fig 2. Process flow of NFT based image classification

[5] Scope of research

The scope of reviewing deep learning for Non-Fungible Token (NFT) classification is expansive, encompassing a range of critical considerations that pertain to the efficacy, challenges, and future prospects of employing deep learning techniques in this domain. Deep learning's role in NFT classification holds immense promise due to its ability to automatically learn hierarchical features from complex visual data. Convolutional Neural Networks (CNNs) and advanced architectures like Residual Networks (ResNets) have demonstrated exceptional performance in image classification tasks, making them well-suited for the intricate and diverse nature of NFT images. A comprehensive review would delve into the various deep learning models used, their architectures, and how they contribute to accurate and efficient classification in the context of NFTs. The review would also need to address the challenges associated with employing deep learning in NFT classification. Issues such as image space consumption, time consumption, and the need for large, labeled datasets pose practical challenges that require careful consideration. Evaluating strategies for mitigating these challenges, such as image compression, noise removal, and transfer learning, becomes an integral part of the review. Additionally, an exploration of the impact of preprocessing techniques on deep learning models for NFT classification is vital. Image compression, noise filtering, and other preprocessing steps play a crucial role in optimizing data for effective model training and inference. Understanding how these techniques contribute to improved accuracy and efficiency is key to providing a comprehensive overview of the scope of deep learning in NFT classification. Beyond the current state of the field, a forward-looking review would discuss potential future directions and emerging trends. This could include advancements in model architectures, the integration of multimodal data (such as text or audio associated with NFTs), and the exploration of explainable AI techniques to enhance transparency and interpretability in NFT classification models.

[6] Conclusion

A thorough review of deep learning for NFT classification should cover the existing models, their performance, challenges faced, and potential solutions. It should also explore the broader scope by considering the future directions and innovations that could further elevate the effectiveness of deep learning in classifying and understanding the diverse landscape of NFTs. Such a review provides valuable insights for researchers, practitioners, and stakeholders aiming to leverage deep learning in the evolving realm of NFT technology.

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