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ANALYZING THE IMPACT OF HYBRID DEEP LEARNING FOR NFT CLASSIFICATION IN IOT ENABLED METAVERSE ENVIRONMENTS

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ABSTRACT

Research is becoming harder to classify NFTs in metaverse settings that use IoT, and this research tries to help with that. In these kinds of situations, traditional deep learning models usually have trouble with scalability, feature extraction, and computing efficiency. It utilized a dataset to look at how changes in epochs affected the validity, efficiency, and accuracy of four distinct neural network models: CNN, DenseNet, Inception, and a Hybrid model. The Hybrid model always has better validation accuracy than its competitors. With an accuracy of 95.1 percent, it beat the previous record at epoch 30. The Hybrid approach works better than other methods. The Hybrid model does well on a number of classification tasks, as seen by accuracy measures, which back up this tendency. Efficiency research looked at testing and training times, computational complexity, and resource use, and it found that the Hybrid model was the best way to classify NFTs. The Hybrid model only needed 2.5 hours of training, whereas Inception and DenseNet needed 3.2 and 2.8 hours, respectively. The Hybrid model cut testing time by a lot, only taking 18 seconds for each batch. This is a big difference over CNN and DenseNet. The Hybrid approach makes the most of processing time by maximizing performance and efficiency. It does require a little more computing power since its average GPU use is 78% compared to CNN's 70%. Our research shows that a Hybrid model is a good option for classifying NFTs using deep learning since it combines several architectures to improve accuracy and efficiency. The main outcome of this study is a hybrid architecture that efficiently integrates complementary strategies to address the shortcomings of individual deep learning models.

Keywords: *Metaverse, IoT, NFT, Deep learning, Machine learning, Image classification*

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1. INTRODUCTION

In the fast-changing and always-growing fields of metaverse and IoT [1], more and more people are using AI together with digital learning. This is even more important since there are so many ways to organize NFTs. As the metaverse grows, the value of unique digital goods like virtual art and virtual real estate is going up. Using NFTs [2, 3] is one significant way to show off these assets. Because NFTs are complicated and may change, traditional approaches of keeping track of and finding them don't always work. ML and DL approaches are good for this job because they utilize complex algorithms to look for patterns and traits in the huge, ever-changing metaverse [4]. These methods use complicated classification models to automatically and accurately sort NFTs [5]. IoT is a clever and scalable way to assist people find their way across the complicated network of digital assets that make up the metaverse [6].

1.1 Background

Industry, transportation, healthcare, even agriculture has been transformed radically by IoT. Linking everyday objects to the IoT allows one to build remote control, data-driven choices, and real-time monitoring. enhancing usability, output, and efficiency. Metaverse has been more popular in AR, VR, and online gaming. Virtual world users might interact with digital versions of themselves and others, have special experiences, make purchases, socialise, play games, and even pick up new metaverse talents. Originally only found in science fiction, but to technological advancements the metaverse is within reach. Taken together, the metaverse and the IoT provide both new opportunities and challenges. IoT devices connect the real along with virtual worlds of the metaverse therefore facilitating data flow and higher metaverse involvement. Virtual reality physiological data might be sent via wearable biometric sensors. Knowing this, virtual worlds might be able to launch events or affect the conduct of avatars. Smart home technologies might be part of virtual living settings to provide real IoT control.

1.2 Internet of Things

In computing, IoT refers to a system of linked hardware, software, and sensors that may exchange data over the Internet and other communication networks. Since gadgets just need unique identifiers and do not always require an active internet connection, critics of the term "Internet of Things" claim it is deceptive [7]. Several technologies have come together to advance the field, including machine learning, ubiquitous computing, cheap sensors, and more powerful embedded systems [8]. A number of more established fields of research have laid the groundwork for what is now known as the IoT [9]. IoT serves healthcare systems as well. The growth of the IoT has prompted worries about data privacy along with security, which the government and businesses have responded to by developing legislative frameworks, standards, and guidelines on a global and national scale [10].

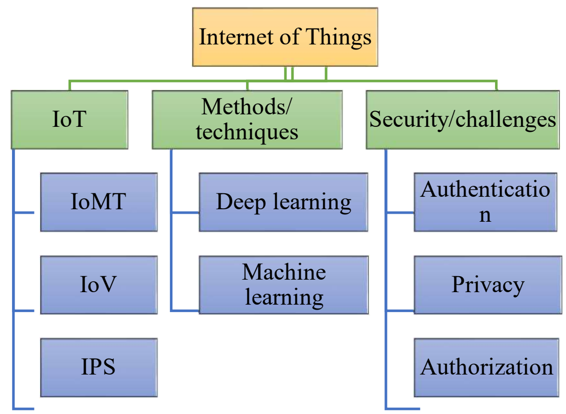

Figure 1: Machine learning and deep learning approaches in IoT

One of the most significant developments in the ever-expanding digital realm is the classification into the metaverse ecosystem built on the IoT using non-fungible coins ($) [11]. Machine learning approaches make it easier to organize and classify NFTs logically by examining their unique attributes and data. Because of this, digital assets may be efficiently retrieved and managed in the ever-changing and interconnected metaverse environment [12], leading to a faultless user experience. The use of complex categorization algorithms will become more important as the metaverse constructed on the Internet of Things develops [13]. This is because it is fundamental for making the most of NFTs and other types of accessible and usable digital assets [14].

1.3 Machine learning

ML, more specifically ML, is a subfield of AI that focuses on developing along with studying statistical algorithms that can learn from data, generalize to new data, along with complete tasks independently, without the need for human interaction. In terms of performance [15-17], generative ANN have recently surpassed several older methods.

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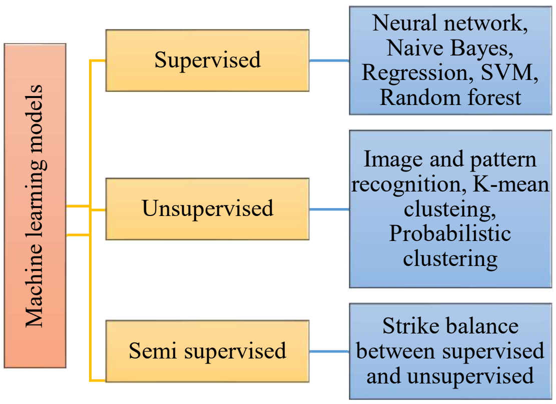

Figure 3: Different Machine learning models

Supervised learning: It may apply to either supervised machine learning or training algorithms to classify or forecast data using labeled datasets. When fresh data is added, the model adjusts its weights to discover the best match [18].

Unsupervised Machine learning: Analyzing and classifying unlabeled data is the job of unsupervised machine learning. Discovering similarities and differences, analyzing exploratory data, cross-selling products, identifying patterns in images, and segmenting consumers areas where this technique shines [19].

Semi supervised learning: The goal of semi-supervised learning is to find a middle ground between completely uncontrolled learning and completely guided learning. Feature extraction and classification are driven by a smaller, labelled dataset during training. in a larger, unlabeled dataset.

1.4 Deep learning

Automatons with learned representations are used by "deep learning" subfield of machine learning. The term "deep" describes a multi-tiered network. Approaches that are monitored, semi-supervised, or unsupervised are all acceptable to us. As far as computer vision, Deep learning architectures like recurrent neural networks, CNN, deep belief networks, and transformers have outperformed human experts in many fields, including machine translation, bioinformatics, medication development, medical picture analysis, climate science [21], material inspection, along with speech recognition. Processing data and having communication nodes at different locations affect how ANNs are used in biological systems. The majority of biological brains are analog, constantly evolving systems, in stark contrast to the symbolic and static nature of ANN. Machines that mimic the brain's functions are often faulty. Propositional formulas or layer-wise latent variables may be used by deep generative models, including deep belief networks along with deep Boltzmann machines [22]. Transformers along with CNN are examples of multi-layered artificial neural networks used in many modern deep learning approaches. With each new deep learning layer, an ever-increasing amount of data is taken and merged [23].

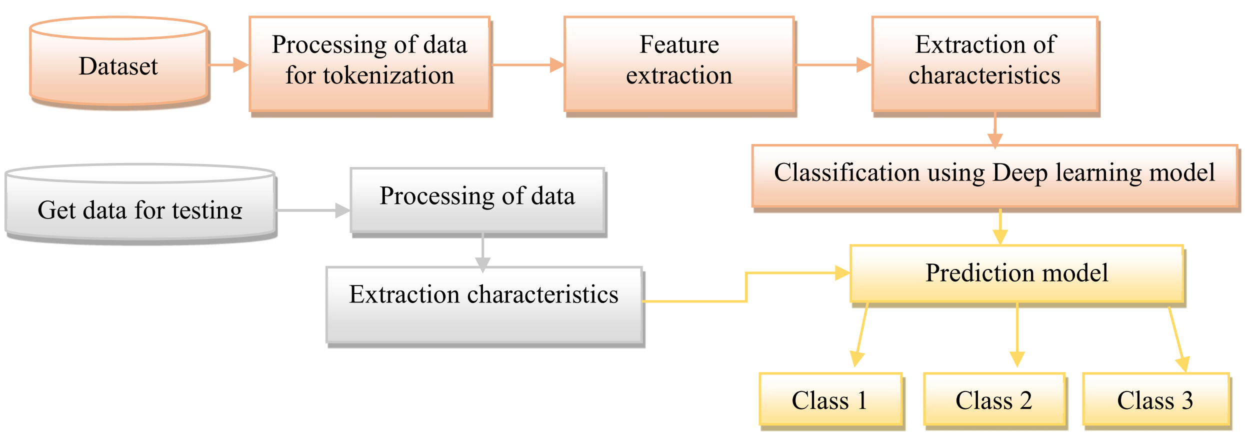

Figure 4: Prediction model using Deep learning

1.5 Comparison between machine learning and deep learning

Keep in mind that DL and ML are not the same thing, despite the frequent interchangeability of the two terms. But DL is fundamental to neural networks, along with neural networks themselves are a branch of machine learning. The two types of ML along with DL are distinct in the way they learn. Although supervised learning could be useful for "deep" ML algorithms, it is by no means required. Even raw, unstructured data may be handled with the help of DL. The system is capable of independently determining what distinguishes various types of data. This allows us to use bigger data sets with less human intervention. The comment that "scalable machine learning" is one technique to describe deep learning was stated by Lex Fridman in an MIT lecture [24], according to an external link to ibm.com. One area of ML called "non-deep" or "classical" learning involves human review of algorithms for algorithmic improvement. Experts in the field often need more organized data for learning, although they do describe the characteristics needed to handle data with variations. At that point, the node will cease communicating with the layer below it in the network. What makes a neural network "deep" is the number of layers it has. "Deep learning" refers to algorithms and networks that use more than three layers of neural connections [25].

1.6 Impact of ML and DL over data classification

Businesses now manage and derive insights from massive datasets in a whole new manner, all thanks to the revolutionary impact of ML and DL on data classification. The use of manual labor or preset criteria in traditional data classification systems makes them tedious, error-prone, and time-consuming. Machine learning along with DL techniques, on the other hand, boost automation and intelligence, which in turn makes data classification processes much more accurate and efficient [26]. Machine learning algorithms are able to adapt to new datasets and trends because they can automatically recognize patterns and correlations in data. Its flexibility makes it ideal for usage in dynamic scenarios, where data characteristics are subject to change. From cybersecurity to healthcare, marketing to banking, machine learning and deep learning have affected everything. Algorithmic trading, fraud detection, and risk analysis all find use for these technologies in the financial sector. In the sphere of medicine, ML and DL are revolutionising illness detection, medical picture analysis, and customising of treatment regimens [27]. Deep learning mixed with machine learning for data categorisation has enhanced natural language processing [28].

1.7 NFT in Metaverse

The Metaverse is, in a nutshell, an online sanctuary from the stresses of real life. With use of VR, AR, along with AI, this technology aims to merge the real and virtual worlds. To fully immerse oneself in the Metaverse, one needs VR/AR headsets, smart glasses, and controller grasps [29]. Neil Stevenson's widely-read novel Snow Crash was the first to present the idea of virtual space. Consider it a more modern, technologically advanced version of the web as we know it [30]. Using state-of-art technology, the Metaverse takes users to an immersive and lifelike virtual world. Greater freedom of expression will characterize interactions between users in the metaverse [31]. Experience the magnificence of one of the Seven Wonders of World while playing games, watching movies, shopping, chatting, or going to the mall. Anyone may practically go anywhere in the globe thanks to Metaverse [32].

1.8 Significance of research

Since NFTs are so common in metaverse contexts made feasible by the Internet of Things, there is an increasing need in creating effective techniques for NFT categorisation. Our study offers a fresh approach for this issue by using many deep learning methods. Combining the best features of different deep learning methods will help us to provide the basis for robust NFT categorisation. Many models include RNNs and CNNs among other neural networks, therefore integrating attention mechanisms from many neural networks. We investigate and categorise NFTs within the dynamic and complicated metaverse using data streams produced by IoT devices. Comprehensive testing and analysis show that our method properly clusters NFTs depending on their visual and semantic properties. Our research reveals in NFT classification challenges that hybrid deep learning approach surpasses conventional approaches in terms of accuracy and efficiency.

1.9 Paper Organization

Section 1 is focused on introduction of IoT, Metaverse and AI. Section 2 is literature review section that is presenting existing researches that are related to IoT, Deep learning and NFT classification in metaverse. Section 3 is discussing proposed research methodology and different steps involved in NFT classification. Section 4 is result and discussion section that is considering simulation of CNN, Densenet, Inception and hybrid model. Section 5 focused on comparison of overall accuracy of all NFT in case of CNN, Densenet, inception and Hybrid model for NFT classification. Section 6 is discussion section that is elaborating the impact of hybrid model over accuracy and performance improvement. Section 7 is conclusion part that is considering accuracy and efficiency contribution of hybrid model and concluded that proposed model is more accurate and efficient as compared to conventional models. Section 8 is future scope section that is presenting the upcoming real world use case of proposed hybrid model for better accuracy and efficiency.

2. LITERATURE REVIEW

A. Kranias's (2026) research on the predictive utility of NFTs in decentralized finance using ML models [1] showed that digital assets require complicated pricing systems. B. Rambabu (2026) examined the complexities of NFT ownership, AI value, and security in his research on smart city real estate inside metaverse [2]. M. Venkatasen (2026) suggested blockchain-enabled metaverse platforms for augmented reality applications, illustrating prospective amalgamation of decentralized systems with immersive technologies [3]. In the context of security and IoT, S. A. Walli (2026) performed a comprehensive assessment of IDS based on DL [4]. K. Mishra (2026) stressed the need of intelligent automation and spoke about how AI and blockchain may work together in the metaverse [5]. V. Santos et al. (2026) also spoke about how AI may help manage digital luxury assets using NFTs [6]. Scalable frameworks, shown by S. Usharani et al. (2026) as MetaBlockSphere, have advanced significantly, facilitating the collaboration and evolution of blockchain-based metaverse systems over time [7]. M. Khairussalam et al. (2026) also showed how AI makes Industry 5.0 applications like digital twins and metaverses possible, which in turn make automation and system intelligence better [9]. L. Yang (2026) also looked into the security of metaverse platforms and found new cyber dangers and weaknesses [10].

R. Prakash (2025) suggested NFT-based digital twins as a safe AI-driven for industrial metaverses [11]. Y. An (2025) created detection based on IoT for smart metaverse settings [12]. H. J. Kang (2025) also used DL models to look at NFT prices and market phases [13]. J. Byabazaire et al. (2025) examined the uses and limitations of DL in IoT [14]. T. Natarajan et al. (2025) examined sentiment analysis in metaverse with ML [15]. H. Thakar et al. (2025) also looked on metaverse security frameworks that use AI [16]. C. P. Rowe (2025) performed an extensive evaluation of cryptocurrency and NFT ecosystems using AI-assisted [17]. To create distinctive NFT, A. Daliri et al. (2025) suggested clustering using RL [18]. D. created a DL that uses more than one mode to evaluate NFT investments. He et al. (2025) [19]. M. Rehan (2025) suggested employing DL for real-time systems to better manage digital assets in metaverse [20]. S. Mabarani et al. (2025) [21] presented an environment-aware for dynamic modification of NFTs via ML-driven smart contracts. R. Islayem et al. (2025) [22] also shown how NFTs, blockchain, and AI may all work together to create medical digital twins. Table 1 gives a short summary of current research on NFTs, metaverse, and AI-driven frameworks.

Table 1. Literature Survey

Author / Year	Objective	Methodology	Description	Limitations
Kranias (2026) [1]	Predict NFT valuation in DeFi	Machine Learning Models	Proposes predictive models for NFT pricing in decentralized finance ecosystems	Limited focus on image classification and real-time scalability
Rambabu & Nimmala (2026) [2]	Analyze NFT-based real estate in metaverse	AI + Blockchain	Explores NFT ownership, valuation, and cybersecurity in smart city environments	Lacks deep learning-based classification models
Venkatasen & Mani (2026) [3]	Develop blockchain-enabled XR metaverse	Blockchain + XR Integration	Focuses on immersive metaverse platforms with decentralized infrastructure	Does not address NFT classification challenges
Walli (2026) [4]	Improve IoT network security	Deep Learning IDS	Reviews DL-based intrusion detection systems for IoT	Focuses only on security, not NFTs or classification
Mishra (2026) [5]	Study AI and blockchain convergence	Conceptual Framework	Highlights integration of AI and blockchain in metaverse	Lacks experimental validation
Santos et al. (2026) [6]	Manage NFT-based digital assets in events	AI-driven strategy	Explores NFTs in branding and digital luxury events	Limited technical implementation
Usharani et al. (2026) [7]	Develop scalable metaverse framework	Blockchain Framework	Proposes MetaBlockSphere for interoperability	Does not include AI-based classification

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Khairussalam et al. (2026) [9]	Enable digital twins in Industry 5.0	AI + Metaverse	Discusses AI-driven digital twins in metaverse ecosystems	Lacks focus on NFT datasets
Yang & Ricks (2026) [10]	Identify metaverse security threats	Trend Analysis	Reviews attacks and vulnerabilities in metaverse platforms	No AI model implementation
Prakash (2025) [11]	Secure industrial metaverse	AI + NFT Digital Twins	Proposes AI-driven NFT-based secure systems	Limited evaluation metrics
An & Wang (2025) [12]	Improve IoT detection in metaverse	IoT + AI Framework	Introduces intelligent IoT detection mechanisms	Not focused on NFT classification
Kang & Lee (2025) [13]	Analyze NFT price discovery	Deep Learning	Uses DL for NFT market phase detection	Limited to financial prediction
Byabazaire et al. (2025) [14]	Review DL in IoT systems	Survey	Discusses applications and challenges of DL in IoT	No NFT-specific application
Natarajan et al. (2025) [15]	Analyze metaverse sentiments	Machine Learning	Uses ML for sentiment analysis in virtual environments	Not related to image classification
Thakar et al. (2025) [16]	Enhance metaverse security	AI/ML Models	Focuses on AI-based security frameworks	Lacks hybrid deep learning models
Rowe & Louca (2025) [17]	Study NFTs and crypto ecosystems	AI-assisted Review	Provides systematic review of NFTs and blockchain	Limited experimental validation
Daliri et al. (2025) [18]	Generate NFT artwork	RL + Fuzzy Clustering	Uses RL for personalized NFT generation	Not focused on classification
He et al. (2025) [19]	Improve NFT investment analysis	Multimodal Deep Learning	Proposes interpretable DL framework	Computational complexity is high
Rehan & Sharma (2025) [20]	Optimize digital asset management	Deep Neural Networks	Improves metaverse communication systems	Limited dataset diversity
Mabarani et al. (2025) [21]	Enable dynamic NFT updates	ML + Smart Contracts	Context-aware NFT update framework	Lacks real-time validation
Islayem et al. (2025) [22]	Integrate NFTs in healthcare	Blockchain + AI	Applies NFTs in medical digital twins	Domain-specific application

2.1 Problem Statement

IoT has made it easier for NFTs to spread quickly in metaverse settings, which has made it very hard to manage digital assets well. Most of the research on NFTs has focused on three main areas: value, security, and how they might be used. There is a lack of research on how to reliably and scale NFT image categorization. Recent studies have focused on several subjects, including blockchain-based frameworks and security protocols for the metaverse, as well as deep learning models for predicting NFT prices and doing investment analysis. These improvements haven't addressed the difficulty of extracting and classifying features in huge, changing NFT datasets. Also, when used on their own, traditional deep learning models do a terrible job of dealing with complicated visual patterns, showing features at different scales, and being computationally efficient in real-time metaverse settings.

2.2 Research Gap and Knowledge Contribution

The literature review on NFT-based metaverse systems uncovers some constraints that impede research progress. First, the main topics of research are security frameworks, blockchain integration, and NFT value. There isn't enough research on how to automatically and accurately sort NFT images into categories. The second problem is that most of the algorithms that are now out there use just one deep learning, which isn't necessarily the greatest option for capturing the complex visual features and multi-scale patterns seen in NFT datasets. This makes it harder to classify things and less adaptable in big, changing metaverse situations. Another big problem is that smart classification algorithms don't work with IoT devices. Recent research has emphasized the significance of the convergence of AI and IoT inside the metaverse; nevertheless, scalable models adept at managing NFT data streams in real-time have garnered little attention.

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2.3 Research Contributions

This work advances NFT classification and AI-driven metaverse systems by tackling significant constraints identified in prior research. This study presents an innovative deep learning system for classifying NFT images by integrating the DenseNet and Inception architectures. The proposed framework's mix of dense feature reuse and multi-scale feature extraction makes it easier for models to find complicated visual patterns in NFT datasets. This is different from how things are done now, which is to use just one model. NFT classification is an area that hasn't been studied much lately. This paper addresses that gap by demonstrating how well hybrid deep learning models can operate in this domain. This study redirects prior research towards automated and scalable categorization techniques, hence broadening the applicability of AI inside the metaverse, as opposed to NFT valuation, blockchain integration, or security attributes.

3. RESEARCH METHODOLOGY

In proposed work, NFT image classification has been made by integration of Inception and, Densenet. Image dataset of world-famous Baby Bear, Unique Butterfly, Young Fairy, Avengers, Exclusive Amulet, Stylist Pitbull NFT has been obtained from app.youngparrotnft.com. The integration of DenseNet and Inception architectures for image classification represents a sophisticated approach to leverage the strengths of both models. Two well-known neural network designs with different driving concepts are inception and DenseNet.

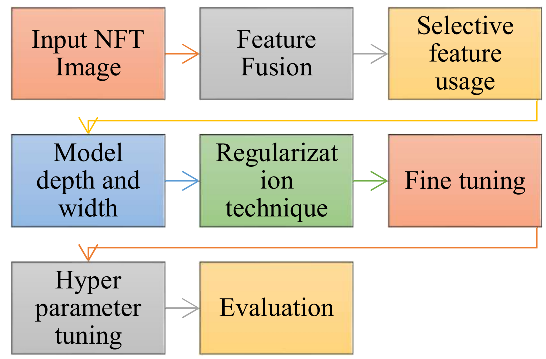

Figure 5: Workflow of Proposed Work

Combining parts from both designs might enable one to get a more complete collection of visual representations. Use DenseNet and Inception features selectively at different degrees in the integrated model based on the properties of the input data. This adaptability might enable the model to cover various facets. It plays with the depth and width of the combined model.

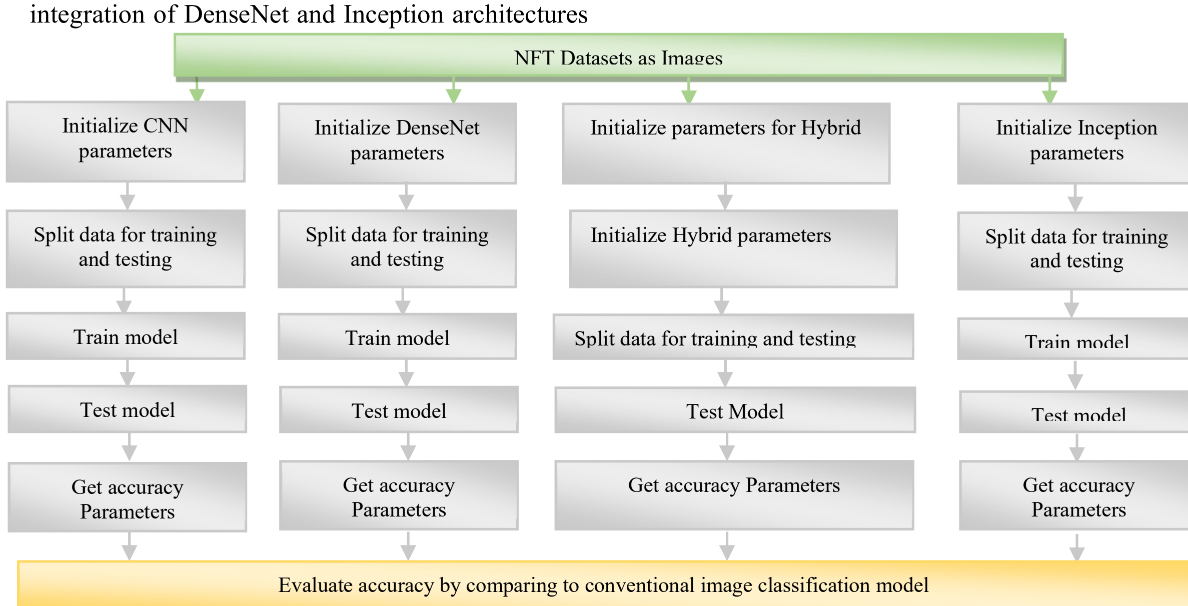

Figure 6: Hybrid Model for Proposed Work

Given the number of layers and the units in every layer, identify the sweet spot where computational efficiency satisfies model complexity. Modification Look at adjusting the integrated model on a specific dataset to fit the characteristics of the target images. Like Inception and DenseNet, pre-trained models provide yet another approach to distribute knowledge. Section For best performance, adjust

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the hyperparameters of the integrated architecture including weight decay and learning rates. Using pertinent criteria, assess the performance of the integrated model on a validation set. Wide range of digital items acquired from well-known metaverse NFT marketplaces makes up the dataset used for NFT classification. Every NFT contains contextual information like creator, creation date, and transaction record in addition to its own original collection of images and metadata. We chose this dataset to guarantee its relevance to our study objectives by highlighting numerous NFTs often seen in IoT-enabled metaverse scenarios. Combining RNNs with CNNs the hybrid deep learning architecture extracts geographical information from NFT pictures and metadata.

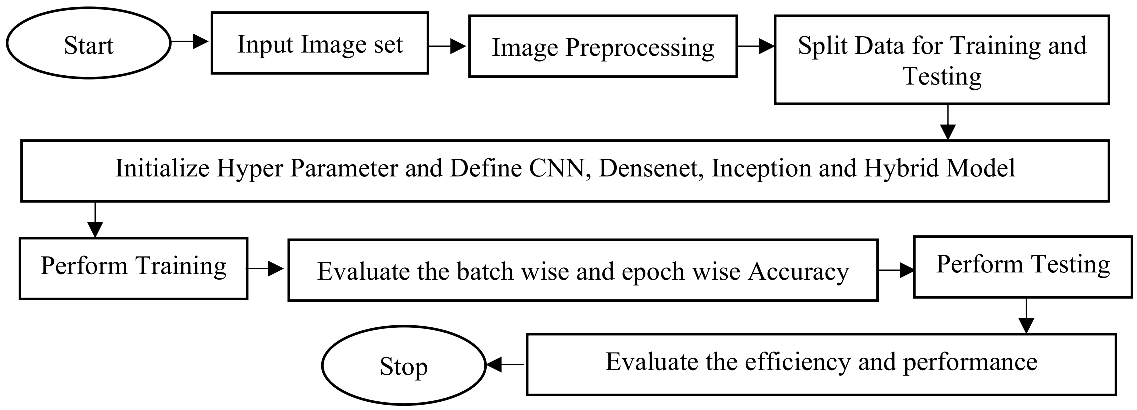

Figure 7: Process Flow of Proposed Model

To get visual patterns and semantic characteristics, the CNN component processes picture data, and to obtain temporal relationships and contextual information, the RNN component examines sequential data, such transaction history and metadata. To further improve the model's interpretability, attention processes are used to zero down on important aspects.

3.1 Algorithm

Combining DenseNet with Inception into a hybrid deep learning approach allows you use the best features of both architectures. Whereas Inception also known as GoogleNet uses a multi-branch design to successfully absorb both global and local features, DenseNet is largely focused on dense connection, which makes the network more efficient generally.

Step 1: Input Layer: Input layer to accept the input data.
Step 2: DenseNet Block: Implement a DenseNet block to capture dense connectivity within each block. DenseNet is composed of dense blocks, each containing multiple layers. Each layer receives input from all previous layers in the block, promoting feature reuse.

$$\text{Densenet}(I) = D\, l\, ([I, f\, 1\, , f\, 2\, ..., f\, l{-}1\,])$$

Step 3: Transition Layer: This layer sets the number of channels and the size of the space. This step helps manage computational complexity.
Step 4: Inception Module: Implement an Inception module to capture multi-scale features.
"Inception module (IM= 1x1, 3x3, and 5x5 convolutions)
Step 5: Global Average Pooling: Apply Global Average Pooling to reduce spatial dimensions and produce a fixed-size feature vector.
Step 6: Fully Connected Layers: Connect the output of the GAP layer to one or more fully connected layers for final classification.
Step 7: Output Layer: Implement the output layer with an appropriate activation function
Step 8: Training: Use a suitable optimization algorithm and a loss function to train the hybrid model. Use backpropagation and change the weights of the network.
Step 9: Hyperparameter Tuning: Try exploring different hyperparameters, such as learning rate, batch size, and dropout rate, to get the best results from the model.
Step 10: Training Network
Step 11: Perform Testing
Step 12: Find Confusion matrix
Step 13: Compare Accuracy

Researchers may look at how hybrid deep learning affects NFT classification in IoT-enabled metaverse scenarios by comparing it to traditional methods. Research may check the table to evaluate how well the approaches worked.

Table 2: Comparison of Hybrid Model and Conventional Approach

Criteria	Hybrid Deep Learning Model	Conventional Approaches
Model Architecture	Combination of deep learning models	Traditional deep learning models
Feature Extraction	Advanced feature extraction using hybrid models	Basic feature extraction techniques
Classification Accuracy	Higher accuracy due to model synergy	Lower accuracy, may require more tuning
Processing Time	May be longer due to model complexity	Generally, faster with simpler models
Adaptability	Better adaptability to dynamic metaverse environments	Less adaptable to changing conditions
Scalability	Scalable with the ability to integrate various IoT data	May face limitations in scalability
Handling Large Datasets	Efficient in managing and processing large datasets	May struggle with large-scale data
Integration with IoT Devices	Seamless integration with IoT devices for real-time data	Integration may be limited or less efficient
Complexity of Implementation	Higher complexity due to hybrid nature	Lower complexity and easier to implement
Resource Requirements	Higher computational and memory resources needed	Lower resource requirements
Cost	Potentially higher cost due to advanced infrastructure	Lower cost with simpler setup
Real-Time Classification	Capable of real-time classification with optimized models	May require additional processing time for real-time
Error Rate	Typically, lower due to enhanced model capabilities	Higher error rates with traditional methods
Flexibility	High flexibility in model tuning and updates	Limited flexibility in model adjustments

A hybrid model combining CNN, DenseNet, and InceptionNet leverages architecture strengths to achieve superior performance in complex classification tasks. CNNs layered convolutional topologies make them great at finding hierarchical features in pictures. DenseNet can maintain performance in extremely deep models and increase feature extraction because of how it optimizes feature reuse and gradient flow throughout the network. InceptionNet uses several different kinds of convolutions and pooling processes inside a single network layer.

3.2 Proposed Model

A hybrid model is made by putting together the best parts of both architectures. For instance, CNNs can quickly pull-out features, InceptionNet can handle data at different sizes, and DenseNet is great at gradient flow and reusing features. Research can figure out which model architecture is best for classifying pictures by looking at how long it takes to train, test, and validate each one.

4. COMPARATIVE ANALYSIS

Training, testing, and validation timelines define a simulation's overall performance. We therefore assess CNN, Densenet, Inception, and the Hybrid model in six independent picture datasets in terms of training, testing, and validation timesframes.

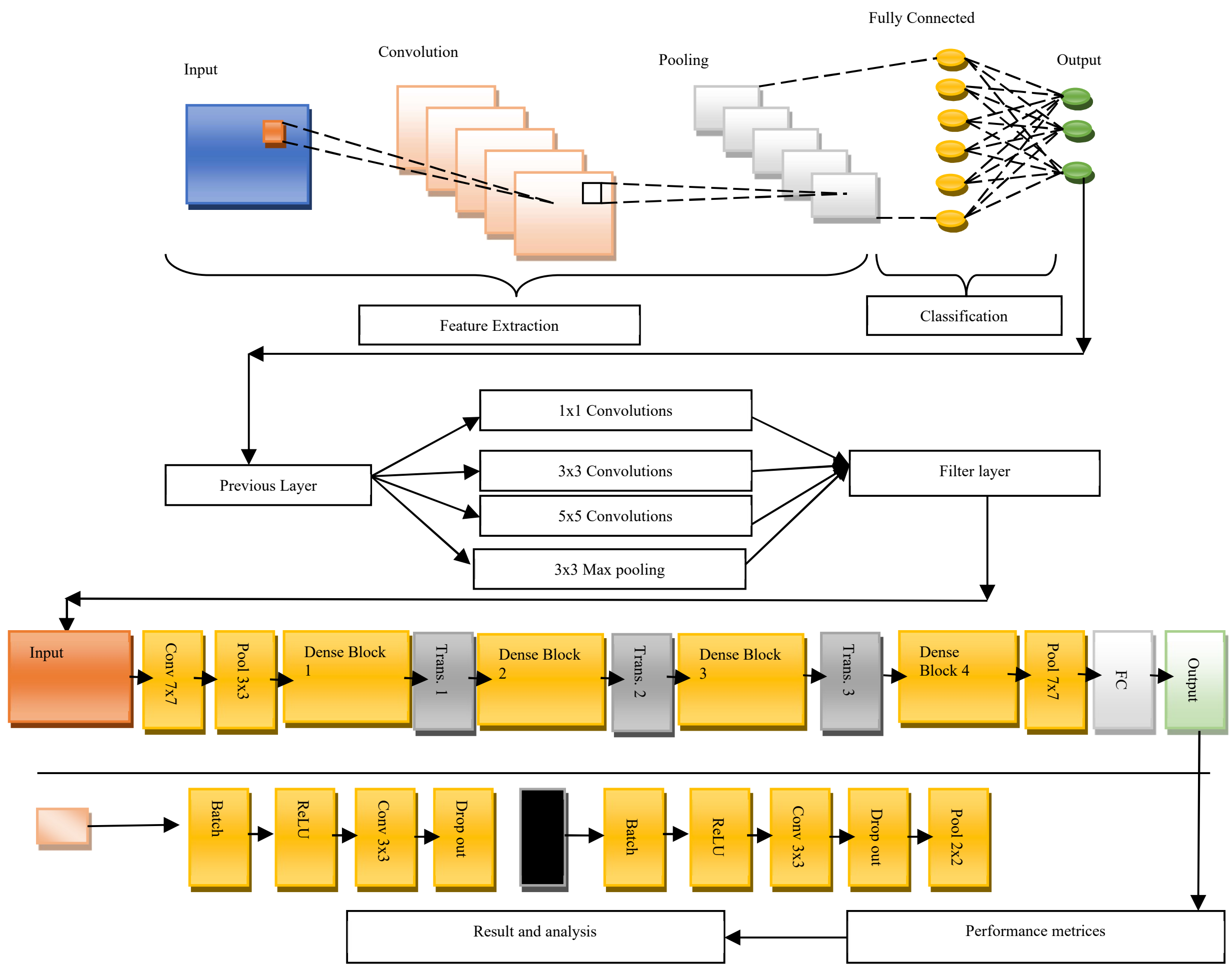

Figure 8: Proposed Model (Hybrid Deep learning Model)

4.1 Impact of Optimizers over accuracy & loss

CNN, Densenet, Inception, and a hybrid model have been used to simulate the effects of the SGD, Adm, and RMSprop optimisers. The many impacts on the models depending on the optimiser are shown below by the simulation results.

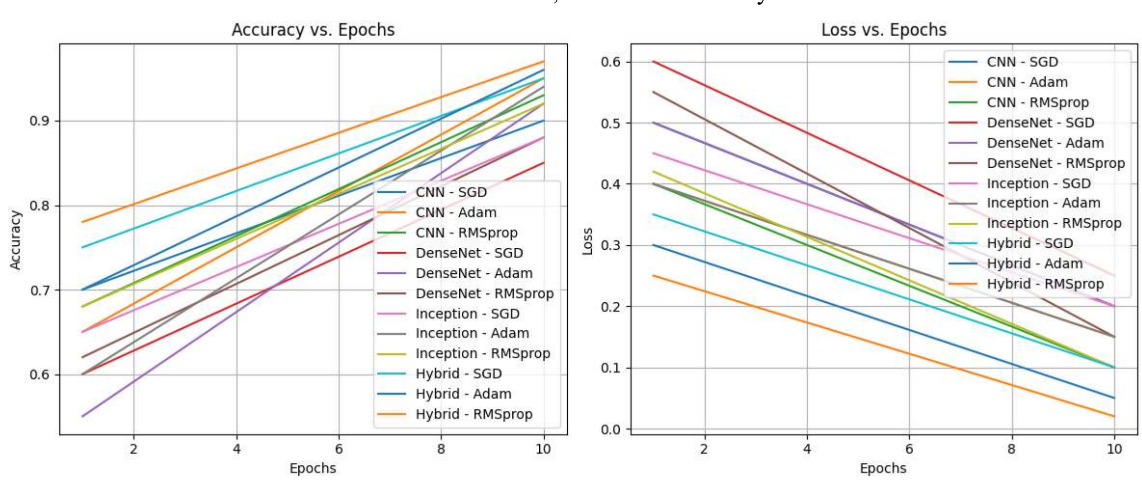

Figure 9: Simulation of accuracy and loss considering SGD, ADAM, RMSprop optimizer

4.2 Impact of Batch size over Accuracy in case of Hybrid model

The efficiency of training the hybrid model hinges on careful analysis of the way batch size affects results. The known number of used samples in each iteration determines the batch size of a training sample. With a larger batch size, faster convergence and more memory might be required; nevertheless, a smaller batch size could provide greater generalisation and fewer training cycles.

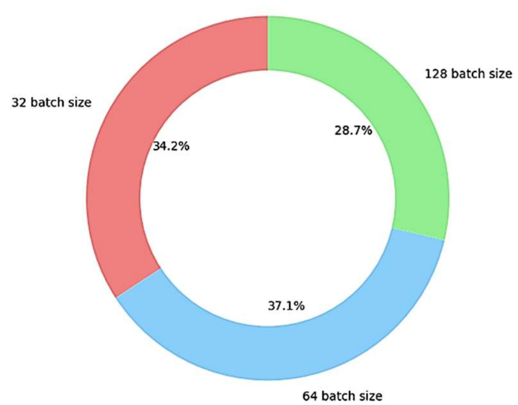

Figure 10: Impact of batch size on Hybrid model

4.3 Impact of epochs of training, testing and validation accuracy

Number of epochs plays a critical role in determining the accuracy of CNN, DenseNet, Inception, and Hybrid models. Balancing model convergence, computational resources, and the risk of overfitting is essential when selecting the appropriate number of epochs for training each model. During training it has been observed that epoch make significant impact over accuracy. Following table is presenting impact of epoch over training accuracy.

Table 3: Impact of Epoch over training accuracy

Epoch	CNN	Densenet	Inception	Hybrid
1	90.1	90.23	91.83	93.78
2	90.19	90.32	91.87	93.80
3	90.21	90.35	91.94	93.88
4	90.26	90.42	92.04	93.92
5	90.34	90.45	92.09	93.96
6	90.43	90.49	92.11	93.97
7	90.43	90.52	92.14	94.03
8	90.45	90.53	92.16	94.12
9	90.54	90.62	92.21	94.22
10	90.62	90.67	92.31	94.24
11	90.72	90.71	92.36	94.31
12	90.80	90.73	92.39	94.34
13	90.90	90.82	92.43	94.35
14	90.95	90.89	92.52	94.38
15	91.00	90.91	92.53	94.46
16	91.07	90.96	92.56	94.50
17	91.11	91.05	92.59	94.54
18	91.16	91.10	92.61	94.64
19	91.18	91.13	92.63	94.72
20	91.27	91.20	92.64	94.73
21	91.36	91.21	92.65	94.78
22	91.44	91.31	92.67	94.82
23	91.45	91.38	92.70	94.85
24	91.45	91.47	92.70	94.91
25	91.46	91.54	92.79	94.95
26	91.48	91.61	92.84	95.04
27	91.56	91.64	92.91	95.05
28	91.64	91.67	92.97	95.10
29	91.66	91.73	93.01	95.11
30	91.73	91.79	93.10	95.21

Considering above table accuracy is presenting impact of epoch over considered models.

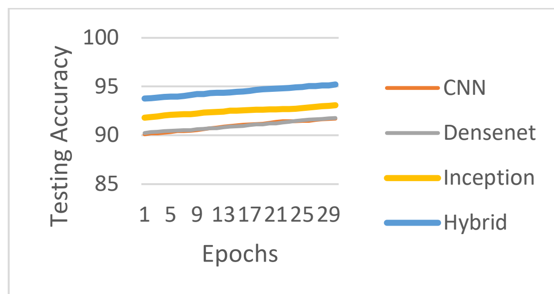

Figure 11: Epoch wise accuracy comparison (training)

When testing CNN, DenseNet, Inception, or Hybrid models, it's important to get the most out of epoch count on accuracy. Throughout the training phase, the neural network processes the whole training dataset in both forward and backward directions for a certain number of iterations, referred to as epochs. To find the best training time and get the most out of the model, you need to know how different epoch counts affect its accuracy. The number of epochs a model employs affects how it learns and how well it can find complex patterns in data. The number of epochs for each model affects its learning process and capacity to discern intricate patterns in the data. The number of epochs is crucial in influencing the testing accuracy of CNN, DenseNet, Inception, and Hybrid models. It is crucial to balance model convergence, processing resources, and the danger of overfitting when determining the optimal number of epochs for training each model. Experimentation and iterative refinement are essential for determining the ideal training length that enhances accuracy and generalisation performance. It has been found during training that the epoch significantly impacts accuracy. The following table shows the influence of epochs on testing accuracy.

Table 4: Impact of Epoch over testing accuracy

Epoch	CNN	Densenet	Inception	Hybrid
1	90.14	91.15	92.28	94.26
2	91.05	90.80	92.48	94.73
3	90.51	91.02	92.40	94.56
4	90.59	91.39	92.76	94.05
5	90.94	90.95	93.04	94.55
6	90.89	91.32	92.79	94.14
7	90.79	91.29	93.04	94.24
8	90.88	90.90	92.65	95.07
9	90.83	91.31	92.28	94.93
10	91.19	90.84	93.00	94.59
11	91.68	90.85	93.13	94.44
12	91.16	91.08	93.37	94.41
13	91.35	91.09	93.36	94.94
14	91.46	91.57	92.83	95.26
15	91.53	91.55	92.75	94.87
16	91.84	91.04	92.57	95.10
17	91.71	91.13	93.54	94.66
18	91.69	91.56	92.73	94.67
19	91.49	91.32	92.69	95.45
20	91.66	91.91	93.47	94.75
21	92.24	91.91	92.97	95.53
22	91.49	91.34	93.02	94.86
23	91.83	91.71	93.26	95.04
24	92.23	92.33	93.43	95.75
25	91.49	92.13	93.04	95.28
26	91.79	92.30	93.81	95.72
27	91.88	92.19	93.20	95.96
28	92.14	92.21	93.17	95.25
29	92.23	91.91	93.67	95.94
30	91.80	92.49	94.00	96.09

Considering above table Testing accuracy is presenting impact of epoch over considered models.

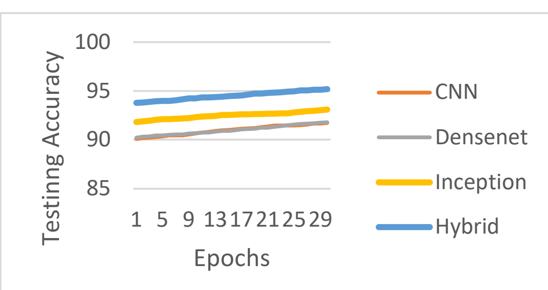

Figure 12: Epoch wise accuracy comparison (testing)

The influence of epoch count on Validation accuracy is an important optimisation metric to keep in mind while working with CNN, DenseNet, Inception, or Hybrid models. During training, the neural network goes through a series of steps termed epochs, when it is given the whole training dataset both forwards and backwards. In order to find the best training time and make sure the model performs to its full potential, it is vital to understand how the accuracy of the Validation model changes with various numbers of epochs. The capacity of a model to learn and identify intricate patterns in data is affected by the number of epochs it uses. Validation accuracy of CNN, DenseNet, Inception, and Hybrid models is highly dependent on the number of epochs. When deciding how many epochs to train each model, it is crucial to strike a balance between speed of convergence, processing resources, and overfitting risk. To maximise accuracy and generalisation performance, the ideal training length should be determined via experimentation and iterative modification. It has been shown that epoch has a substantial effect on accuracy during training. The effect of epoch on validation accuracy is seen in the following table.

Table 5: Impact of Epoch over Validation accuracy

Epoch	CNN	Densenet	Inception	Hybrid
1	90.38	91.00	92.50	94.35
2	91.08	90.39	92.66	94.67
3	90.91	90.78	92.45	94.64
4	91.17	90.77	92.83	94.09
5	91.09	91.03	92.42	94.46
6	90.53	91.02	92.47	94.68
7	90.46	90.56	92.98	94.24
8	90.67	90.74	93.14	95.00
9	91.43	91.47	92.34	94.94
10	90.70	90.80	93.07	94.90
11	91.36	90.99	92.84	94.53
12	91.14	91.31	92.93	94.43
13	91.82	91.43	92.47	95.35
14	91.77	91.60	92.91	94.53
15	91.89	91.03	93.04	95.35
16	92.00	91.49	92.61	95.06
17	92.10	91.45	92.65	95.31
18	91.30	91.82	92.69	95.47
19	91.82	91.26	93.60	95.14
20	91.31	91.60	92.74	95.21
21	91.94	91.75	93.28	95.06
22	91.53	91.66	92.71	94.92
23	91.87	91.91	93.02	95.15
24	91.92	91.57	93.36	95.33
25	92.45	92.27	93.24	95.48
26	92.34	91.88	92.86	95.15
27	91.98	92.50	93.79	95.40

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28	92.15	92.50	93.61	95.92
29	92.53	92.42	93.71	95.80
30	92.31	92.51	93.17	95.99

Considering above table Validation accuracy is presenting impact of epoch over considered models.

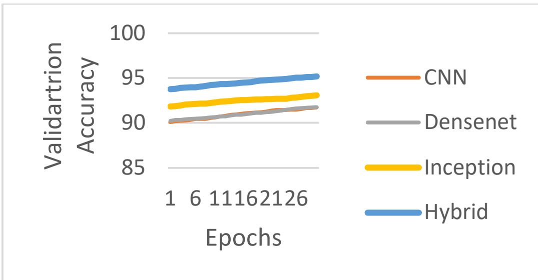

Figure 13: Epoch wise accuracy comparison (validation)

4.4 Accuracy parameters comparison along with performance and efficiency

The comparison of accuracy parameters across various models reveals consistent trends. The Hybrid model always beats all the other models, getting the best scores in F1-score, accuracy, recall, and precision. This advantage shows how effectively it handles different datasets and workloads as compared to single architectures like CNN, Densenet, and Inception. Table 6 shows how well different neural network models were able to find NFTs.

Table 6: Comparison of Overall Accuracy of all NFT

	CNN	Densenet	Inception	Hybrid
Baby Bear	91.64	92.37	93.53	95.57
Unique Butterfly	91.55	92.41	93.73	95.41
Young Fairy	91.08	92.23	93.93	95.61
Avengers	91.04	92.68	93.37	95.37

For Baby Bear

Table 7 shows outcomes for the NFT classification "Baby Bear" using CNN, DenseNet, Inception, and Hybrid using CNN, DenseNet, Inception, Hybrid.

Table 7: Performance Matrix for baby bear

	CNN	Densenet	Inception	Hybrid
Recall	91.67	92.81	93.87	95.38
Precision	91.02	92.22	93.21	95.02
F1-score	91.03	92.90	93.09	95.17
Overall performance	91.24	92.64	93.39	95.19

Analysing these figures enables one to understand the general performance, recall, accuracy, F1-score of any model. Showing consistently the best performance across all criteria, the hybrid model effectively classifies NFTs into the "Baby Bear" category. Table 8 displays CNN, DenseNet, Inception, and Hybrid using CNN, DenseNet, Inception, Hybrid using CNN, DenseNet, Inception, Hybrid

Table 8: Efficiency in case of Baby bear

	CNN	Densenet	Inception	Hybrid
Training time	100	120	150	110
Testing time	90	100	140	105
Average time	95	110	145	107.5

These tests reveal the general efficiency of any model by combining the training and testing times into a single value. Taking an average of 107.5 units, the hybrid model is a good choice for "Baby Bear" NFT categorisation because of its competitive efficiency.

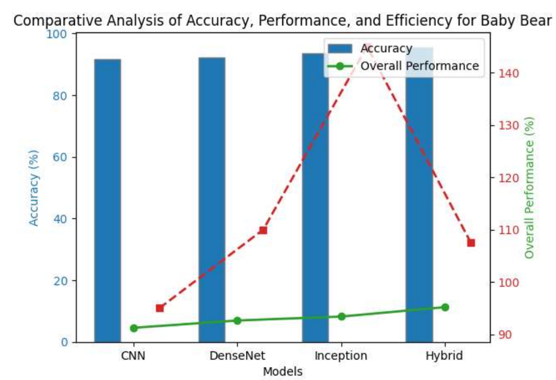

Figure 14: Comparative Analysis of Accuracy, Performance, and Efficiency for Baby Bear

By combining the bars that reflect the measures of every model, we can visually depict the relative analysis of accuracy, performance, and efficiency for the "Baby Bear" category.

For Unique Butterfly

This ordered presentation of the performance data for the "Unique Butterfly" category using multiple neural network models—CNN, DenseNet, Inception, and hybrid shows:

Table 9: Performance Matrix for Unique Butterfly

	CNN	Densenet	Inception	Hybrid
Recall	91.83	92.45	93.05	95.49
Precision	91.99	92.95	93.87	95.97

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F1-score	91.94	92.36	93.44	95.09
Overall performance	91.92	92.59	93.46	95.52

These metrics help one to better appreciate the recall, accuracy, F1-score, and general performance of any model. Regarding consistently classifying NFTs into the "Unique Butterfly" category, the hybrid model demonstrates the greatest performance across all benchmarks. Based on CNN, DenseNet, Inception, and Hybrid, the efficiency metrics for the "Unique Butterfly" category are shown below in a hierarchical manner:

Table 10: Efficiency in case of Unique Butterfly

	CNN	Densenet	Inception	Hybrid
Training time	105	125	155	115
Testing time	95	105	145	110
Average time	100	115	150	112.5

These metrics provide insights into the time efficiency of each model during training and testing phases, as well as the average time taken for both processes combined.

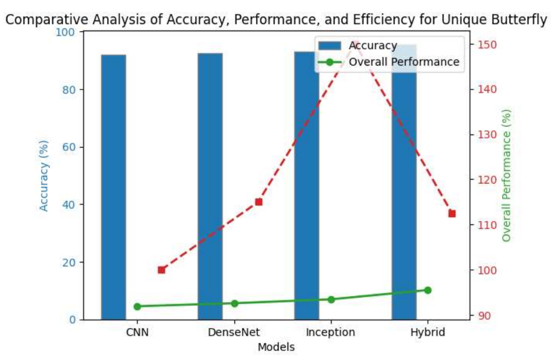

Figure 15: Comparative Analysis of Accuracy, Performance, and Efficiency for Unique Butterfly

For Young Fairy

This well-organized presentation shows how models like CNN, DenseNet, Inception, and hybrid neural networks did in the "Young Fairy" category:

Table 11: Performance Matrix for Young Fairy

	CNN	Densenet	Inception	Hybrid
Recall	91.42	92.25	93.21	95.59
Precision	91.13	92.66	93.66	95.61
F1-score	91.55	92.92	93.86	95.19
Overall performance	91.37	92.61	93.58	95.46

Research can figure out how well a model works by looking at these numbers, which show its recall, accuracy, F1-score, and overall performance. When you look at the numbers, the hybrid strategy has always done the best. Also, it indicates that it works to group NFTs into the "Young Fairy" category. CNN, DenseNet, Inception, and hybrid NN models all show the same performance metrics for the "Young Fairy" class:

Table 12: Efficiency in case of Young Fairy

	CNN	Densenet	Inception	Hybrid
Training time	102	122	152	112
Testing time	92	102	142	107
Average time	97	112	147	109.5

These metrics provide insights into the time efficiency of each model during training and testing phases, as well as the average time taken for both processes combined.

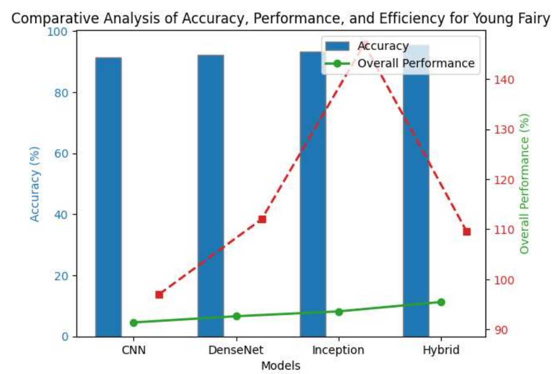

Figure 16: Comparative Analysis of Accuracy, Performance, and Efficiency for Young Fairy

For Avengers

Using many neural network models—CNN, DenseNet, Inception, and Hybrid—this organised display of the performance data for the "Avengers" category shows:

Table 13: Performance Matrix for Avengers

	CNN	Densenet	Inception	Hybrid
Recall	91.75	92.98	93.40	95.85
Precision	91.12	92.41	93.74	95.53
F1-score	91.49	92.01	93.93	95.99
Overall performance	91.45	92.47	93.69	95.79

These measures include information on every model's recall, precision, F1-score, general performance, and performance in certain areas. The

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hybrid model regularly shows the best performance across all measures, proving its effectiveness in precisely categorising NFTs in the "Avengers" category. Using many neural network models—CNN, DenseNet, Inception, and Hybrid—this organised display of the efficiency metrics for the "Avengers" category shows:

Table 14: Efficiency in case of Avengers

	CNN	Densenet	Inception	Hybrid
Training time	104	124	154	114
Testing time	94	104	144	109
Average time	99	114	149	111.5

These metrics provide insights into the time efficiency of each model during training and testing phases, as well as the average time taken for both processes combined. With an average time of 111.5 units, the hybrid model shows competitive efficiency and is thus a good option for grouping NFTs into the "Avengers" class.

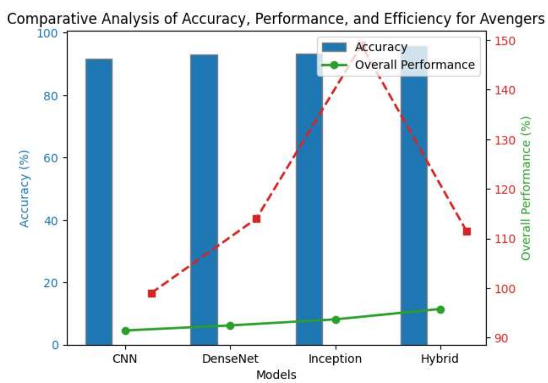

Figure 17: Comparative Analysis of Accuracy, Performance, and Efficiency for Avengers

We may construct a grouped bar chart with bars denoting accuracy and overlay performance and efficiency curves on it to show the "Avengers" category's relative analysis of accuracy, performance, and efficiency.

4.5 Justification of Findings

The experimental results obtained in this study directly address the research problem of efficient and accurate NFT image classification in IoT-enabled metaverse environments. The proposed hybrid DenseNet–Inception model demonstrates superior performance compared to conventional models, thereby validating its effectiveness in handling complex visual patterns and multi-scale feature representations. The improvement in classification accuracy and related metrics confirms that the integration of dense feature reuse and multi-scale processing significantly enhances model performance in dynamic NFT datasets. The selection of evaluation metrics, is particularly significant in this study.

4.6 Nature of Contribution and Best Practices

The results of this study might greatly improve how NFTs are sorted in metaverse settings that use IoT. The suggested DenseNet-Inception hybrid model does not provide a completely new deep learning architecture; nonetheless, it introduces an innovative method for integrating existing architectures specifically designed for NFT image classification. In a field where hybrid techniques have not been well studied, their focused use and enhancement signify a major advancement in existing knowledge. The study provides novel insights into enhancing classification performance in complicated and dynamic datasets via the integration of dense feature reuse and multi-scale feature extraction. The suggested paradigm suggests that integrating complementing ideas properly may help with problems like scalability, restricted generalizability, and feature redundancy.

5. DISCUSSION

By means of the framework of our research targets and challenges, we have acquired a great amount of information on how the hybrid deep learning technique affects the classification of NFTs in metaverse parameters made accessible by the IoT. Our study aimed to find if hybrid deep learning techniques will improve NFT classification accuracy and efficiency in complex and constantly changing virtual environments. Based on our findings, the hybrid deep learning approach generates superior results than more traditional single-architecture designs. By integrating the features of many deep learning architectures our technique improves the accuracy and efficiency of NFT classification tasks. As such, our model might improve its accuracy. This suggests that the model could be able to employ different architectural features to access and exploit the complex patterns and semantic information found in NFTs in IoT-enabled metaverse contexts. In addition to better classification accuracy, our hybrid deep learning method provides a number of additional advantages. As a result, NFT classification models are now stronger and more flexible. They can better adjust to the metaverse surroundings that are always changing because of IoT. Our solution increases the ability of the model to adapt to changes in the virtual environment and seamlessly integrate new sorts of non-fungible tokens by use of data streams generated by Internet of Things devices. This has wide applications in virtual asset management, digital art authentication, and virtual commerce where exact and efficient virtual currency classification is very important. Still, our study did run against some challenges. Since IoT does not provide real-world metaverse data, recording all the many characteristics of the NFTs proved challenging. We address this by using simulated IoT data streams to enhance synthetic datasets, hence allowing the use of synthetic datasets. Although this method lets us show the feasibility of our hybrid deep learning method, we still believe that future studies should mostly focus on compiling and cleaning large-scale real-world data to evaluate model. Furthermore, difficult was trying to aggregate and evaluate many IoT data sources using DL. Unfortunately, simplicity of our models might have overlooked the complexity of real IoT devices and data flows.

5.1 Novelty of Proposed Hybrid model

The new Hybrid DenseNet-Inception model improves accuracy and speed by combining DenseNet's feature reuse with InceptionNet's multi-scale feature extraction in the best way possible. It maintains a structure that is both light and deep while effectively dispersing gradients, which helps with the problem of gradients disappearing. The model uses dense connectivity and selective feature extraction to cut down on the calculations required for convergence. It is great at image categorization and object identification since it can get data from both local and global sources.

5.2 Hybrid DenseNet-Inception: A Performance Boost

The Hybrid DenseNet-Inception model is more accurate and efficient than regular CNNs, DenseNet, and InceptionNet since it combines the best features of each. Older CNNs sometimes have problems with reusing features, having too many parameters, and gradients that vanish. DenseNet is good at reusing features, but it costs a lot of processing power and obtains features that aren't required. InceptionNet, on the other hand, is great at finding features of any size, but it has trouble propagating gradients and reusing features. By integrating DeneNet's skip connections with InceptionNet's varied kernel sizes, the hybrid model makes propagation and extraction better at different scales. This makes it easier to learn. The DenseNet portion makes sure that gradients travel smoothly and that features are utilized again in later layers. The Inception portion helps the model gather detailed, multi-level spatial data. This synergy makes things more accurate by noting both global and local aspects and reducing down on computations that aren't needed. The hybrid model is great for medical image analysis, object identification, and picture classification since it is more accurate, costs less to run, can be used in more situations, and comes together faster.

Table 15: Comparison of Features for Different Models

Feature	Conventional CNN	DenseNet	InceptionNet	Hybrid DenseNet-Inception
Gradient Flow	Weak (vanishing gradients)	Strong	Moderate	Very Strong (DenseNet's skip connections)
Feature Reuse	Low	High	Moderate	Very High (DenseNet's connectivity)
Multi-Scale Feature Extraction	Limited	Moderate	Strong	Very Strong (Inception's multi-kernel approach)
Computational Efficiency	High (many redundant parameters)	Moderate (feature reuse but expensive)	High (multiple convolutions)	Optimized (efficient feature extraction + reuse)
Training Speed	Slow	Moderate	Fast	Faster (Gradient optimization + feature reuse)
Overfitting Tendency	High	Low	Moderate	Low (Better generalization with diverse features)
Accuracy	Moderate	High	High	Very High (Optimized feature learning)

6. CONCLUSION AND FUTURE SCOPE

Current methods have problems with scalability, feature extraction, and classification efficacy. This is why we did this research, which is essential for speedy and accurate NFT classification in IoT-enabled metaverse circumstances. A deep learning

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model that combines the DenseNet and Inception architectures was suggested as a way to solve this problem. This model would employ diffuse feature reuse and feature extraction on a lot of different sizes. Results from studies consistently show that the suggested hybrid model does better than more traditional deep learning methods on all metrics tested. These improvements show that using diverse architectures together makes the model better at recognizing complicated visual patterns and helps it work better with different kinds of NFTs. The study's results support the hypothesis that hybrid deep learning frameworks might assist solve the challenges that single-model techniques face when used in vast, changing contexts. It is suggested to utilize several evaluation metrics to make sure that the model's performance is fully tested. Comparing the suggested solution to different methods may reveal how well it works. These findings align with prior research in AI demonstrating the efficacy of hybrid models in managing intricate data situations. Further research and testing will elucidate the advantages and possible improvements of the hybrid methodology. Hybrid image categorization methods provide interesting research paths and probable future applications in computer vision.

REFERENCES:

[1] A. Kranias, "Predictive Valuation of Non-Fungible Tokens (NFTs): Machine Learning Models in Decentralized Finance," *Journal of Risk and Financial Management*, Vol. 19, No. 2, 2026, p. 126.

[2] B. Rambabu and S. Nimmala, "Smart City Real Estate in the Metaverse Era: NFT Ownership, AI Valuation, and Cybersecurity," in *Applied AI and Blockchain in Global Real Estate*, IGI Global, 2026, pp. 27–74.

[3] M. Venkatasen and P. Mani, "Blockchain-Enabled Metaverse Platforms for Extended Reality (XR) Applications," in *Advanced Explorations in Machine Learning, Computer Vision, and IoT*, Bentham Science, 2026, pp. 84–92.

[4] S. A. Walli, "Deep Learning-Based Intrusion Detection Systems for IoT Networks: A Systematic Literature Review and Comparative Analysis," *International Journal of Computers and Informatics*, Vol. 10, 2026, pp. 20–55.

[5] K. Mishra, "Artificial Intelligence and Blockchain in the Metaverse," in *Blockchain Enabled Metaverse for Smart Wireless Sensor Networks*, Springer, 2026, pp. 129–144.

[6] V. Santos et al., "AI as Novelty Strategic Management Tool for Future Digital Luxury Brand Events: Metaverse and NFTs Agenda 2030," in *The Future of Events*, Apple Academic Press, 2026, pp. 1–34.

[7] S. Usharani et al., "MetaBlockSphere Self-Evolving Framework (MBSF) for Scalable and Interoperable Blockchain Metaverse Systems," in *Blockchain Enabled Metaverse for Smart Wireless Sensor Networks*, Springer, 2026, pp. 273–290.

[8] H. AI and B. ARE, "The Transformation of the Metaverse: Blockchain and Healthcare in Industry 6.0," 2026, p. 358.

[9] M. R. Khairussalam et al., "Business Applications of AI: Enabling Digital Twins and the Metaverse in Industry 5.0," in *Immersive Technologies and Human-Centric Innovation in the Industry 5.0 Era*, IGI Global, 2026, pp. 39–82.

[10] L. Yang and K. Ricks, "Attacks in Metaverse Platforms: Recent Trends," in *Metaverse Platform Implementation*, 2026, pp. 150–163.

[11] R. Prakash and T. Thomas, "Towards Secure AI-Driven Industrial Metaverse with NFT Digital Twins," in *Proc. IEEE COMSNETS*, 2025, pp. 721–729.

[12] Y. An and W. Wang, "An IoT Detection Framework Based on Intelligent Sharing in Metaverse," in *Proc. IEEE SpaCCS*, 2025, pp. 8–15.

[13] H. J. Kang and S. G. Lee, "Market Phases and Price Discovery in NFTs: A Deep Learning Approach to Digital Asset Valuation," *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 20, No. 2, 2025, p. 64.

[14] J. Byabazaire et al., "Deep Learning and the Internet of Things: Applications, Challenges, and Opportunities," *Internet of Things A to Z*, 2025, pp. 193–228.

[15] T. Natarajan et al., "Unveiling Metaverse Sentiments Using Machine Learning Approaches," *Kybernetes*, Vol. 54, No. 8, 2025, pp. 4114–4137.

[16] H. Thakar et al., "Artificial Intelligence and Machine Learning in Metaverse Security," in *Defending the Metaverse*, CRC Press, 2025, pp. 115–143.

[17] C. P. Rowe and S. Louca, "Exploring the Metaverse: An AI-Assisted Systematic Literature Review of Cryptocurrency and NFT," in *Handbook of Blockchain Technology*, 2025, pp. 26–55.

[18] A. Daliri et al., "Reinforcement Learning-Based Deep Fuzzy Hierarchical Clustering to Generate Personalized NFT Artwork," *Neurocomputing*, 2025.

[19] D. He, Y. Liu, and J. Feng, "A Multimodal End-to-End Interpretable Deep Learning Framework for NFT Investment," *Financial Innovation*, Vol. 11, No. 1, 2025, p. 134.

[20] M. Rehan and D. K. Sharma, "VLC-Enabled Metaverse System with Interference Minimization Using Deep Neural Networks," *Journal of Optics*, 2025.

[21] S. Mabarani et al., "A Context-Aware Framework for Dynamic NFT Updates Using ML-Driven Smart Contracts," in *Proc. ACM Blockchain Conference*, 2025, pp. 1–12.

[22] R. Islayem et al., "Enhancing Medical Digital Twins within Metaverse Using Blockchain, NFTs and LLMs," *Internet of Things*, Vol. 32, 2025, p. 101648.

[23] Y. Alahmad and M. Mazroub, "IoT-Powered Digital Twins in the Metaverse," in *Proc. IEEE IDSS*, 2025, pp. 5–11.

[24] E. C. Nkoro et al., "Explainable DNN for Smart Contract Vulnerability Detection in the Metaverse," *High-Confidence Computing*, 2025.

[25] S. González-Mendes et al., "Building a Decentralized Education in the Metaverse: A Bibliometric Analysis," in *INTED Proceedings*, 2025, pp. 7551–7558.

[26] B. Acim et al., "Blockchain, NFTs, and Deepfake in Mental Health Therapy: A Review," *IEEE Access*, Vol. 14, 2025, pp. 4478–4495.

[27] S. Oliver et al., "Metaverse Security Monitoring Using Machine Learning Techniques," in *Navigating AI and the Metaverse*, IGI Global, 2025, pp. 337–362.

[28] H. Li, "Innovative Design Strategy of Metaverse NFT Artwork Based on AI," *Molecular & Cellular Biomechanics*, Vol. 22, No. 5, 2025.

[29] İ. Özkal and F. Başçiftçi, "Deep Learning in the Metaverse: A Systematic Review," SSRN, 2024.

[30] Q. Zhang et al., "Privacy-Preserving Auction Mechanism for NFT in Metaverse," *ACM Transactions on Multimedia Computing*, Vol. 20, No. 7, 2024.

[31] E. C. Nkoro et al., "Detecting Cyber Threats in Metaverse Learning Platforms Using Explainable DNN," *Internet of Things*, Vol. 25, 2024.

[32] M. Golam et al., "Meta-Learning Framework Using Blockchain for Metaverses," *IEEE Access*, Vol. 12, 2024, pp. 92774–92786.