Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

An Integrated Deep Learning Framework for NFT Image Classification and Customer Sentiment Analysis in Digital Commerce

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ARTICLE INFO

Received: 03 Aug 2023

Revised: 17 Sept 2023

Accepted: 28 Sept 2023

ABSTRACT

As NFTs and digital transactions continue to soar in popularity, the demand for smart solutions that can process visual, digital assets and user input in the form of text has become increasingly apparent. Common machine-learning methods need to be pre-engineered in terms of features, and often fail to deal with very complicated visual patterns, domain-specific jargon, sarcasm, mixed emotions, and long-range context relationships. In this paper, an integrated deep learning approach to image classification of NFTs and customer sentiment analysis is presented. When processing, resizing, normalization and augmentation are performed prior to the extraction of high-level visual features, the image is used as the main input.If the image is used as the main input, resizing, normalization, and augmentation are performed beforehand, and then high-level visual features are extracted. For sentiment analysis in text, cleaning, tokenization, normalization, embedding, contextual modelling and multi-class prediction is used. The workflow processes both positive sentiment and negative sentiment as well as neutral sentiment, and uses accuracy, precision, recall, F1-score, confusion matrices, ROC curves and AUC as key evaluation metrics. The study also takes into account transfer learning, feature optimization, class imbalance, domain-specific vocabulary, interpretability, and deployment efficiency. The integrated approach shows improved accuracy and reliability of classification in the study, compared to the isolated and conventional approaches, and it offers a flexible foundation for digital-asset evaluation, recommendation, fraud and anti-fraud control, as well as customer experience management and decision support.

Keywords: NFTs, deep learning, CNN, BiLSTM, Transformer, sentiment analysis, digital commerce, image classification, transfer learning, natural language processing.

1. INTRODUCTION

These reviews, ratings, comments, social media discussions and product descriptions are just some of the vast amounts of unstructured customer data that digital commerce relies on. As data is the lifeblood of traditional, commercial transactions, NFTs have created a new category of digital assets that are marked by visual content, ownership history, provenance, and market engagement [1]. In this digital asset and online commerce context, one can thus visualize a context of analysis in which visual and textual information needs to be processed efficiently [2].

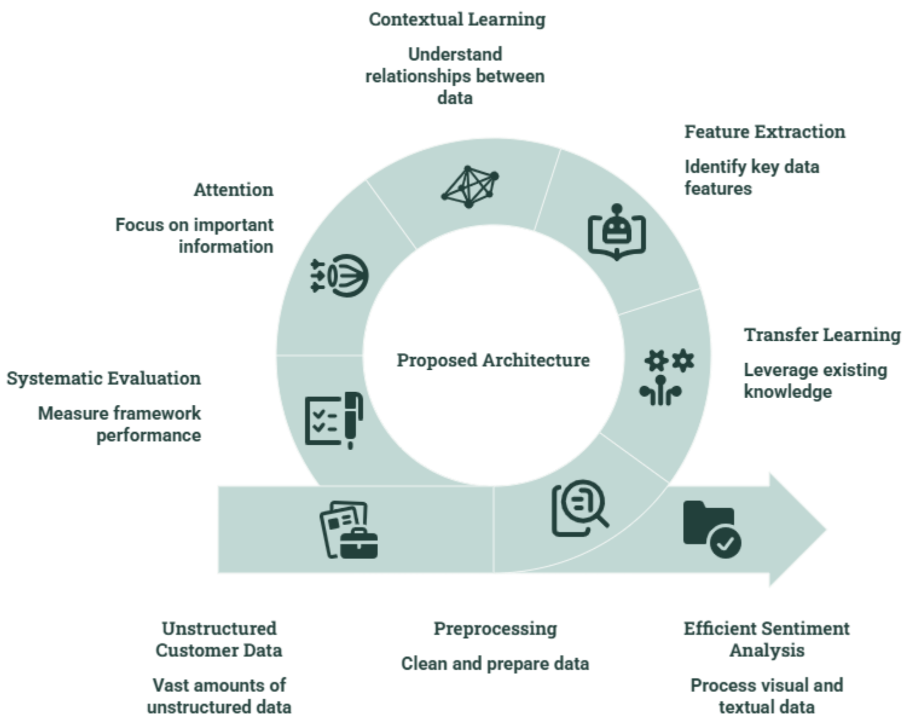

Figure 1: Efficient Sentiment Analysis for Digital Commerce

The overall concept of efficient sentiment analysis in digital commerce is presented in Figure 1. It emphasizes the integration of deep learning methods for analyzing customer feedback and gaining valuable sentiment data [3]. The framework enables a greater understanding of customer opinions, preferences, and experiences. This will help lay the groundwork for intelligent and effective sentiment-analysis solutions to digital-commerce applications.

The fact that positive, negative, and neutral sentiment can be an indicator of satisfaction, trust, perceived value, authenticity concerns, and investment risk makes sentiment a particularly important factor in a customer's perspective [4]. The research framework solves this issue by using multiple classifiers and visual classification and language oriented deep learning. The study discusses the drawbacks of using a single machine learning model and a single deep learning model, and introduces an architecture that is able to extract local features, sequential dependencies and attention-based contextual relationships [5].

The framework is inspired by problems that were found in the research, such as unbalanced and noisy reviews, NFT domain-specific terminology, multilingual and informal language, sarcasm, absence of labeled datasets, complexity of computation, and the black-box of many deep models [6]. The proposed architecture is thus focused on preprocessing, transfer learning, feature extraction, contextual learning, attention, and systematic evaluation. ☐filecite☐turn2file7☐L649-L678☐

1.2. Research Motivation and Problem Definition

In the field of electronic commerce, there are already some sentiment-analysis systems based on traditional classifiers from machine learning or single deep learning architectures [7]. These models are able to detect general sentiment trends, but may fail to perform well if the review is a slang word, an abbreviation, a domain-specific term, an implicit sentiment, sarcasm or multiple emotions. When NFTs talk, crypto, smart contracts, token, gas fees, blockchain, and minting come into play. This is because of the NFT jargon used like minting, blockchain, gas fees, token, smart contracts and cryptocurrency [8].

The research also calls out the shortcomings of the NFT analytics in the image classification, fraud detection, recommendation, and digital asset verification. The conventional image classification is able to identify visual features and does not necessarily model the opinion of users. On the other hand, sentiment analysis models focused on text alone are unable to learn from the visual attributes of digital assets [9]. The ensuing research challenge is then

Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
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to develop a coherent analytical process that can yield meaningful representations from both the digital-asset image and the text of the accompanying materials.

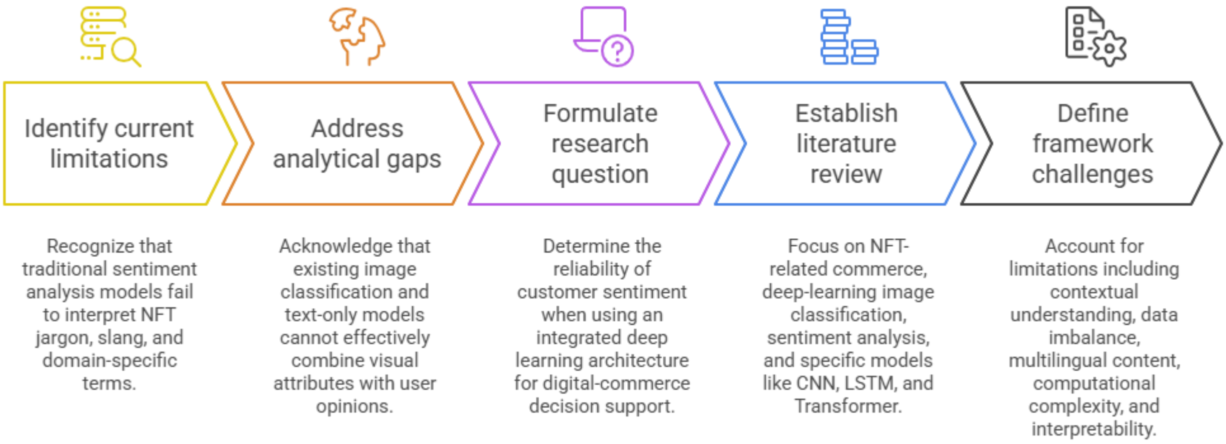

Figure 2: Developing an Integrated NFT Sentiment Analysis Framework

Figure 2 shows the construction of an integrated NFT sentiment analysis system. It presents the concept of how deep learning algorithms can be used to integrate visual aspects of NFTs and text data from customer reviews [10]. The framework is designed to offer a thorough grasp of the opinions of customers and digital assets connected with NFTs. This integrated approach overcomes important shortcomings of the traditional stand-alone analysis techniques. The research question is formulated as follows: What is the reliability and context of customer sentiment around NFTs be, if there is an integrated deep learning architecture that can add support to the practical digital-commerce decision support and also assist in visual asset classification?

The Literature Review in the paper should emphasize on NFT-related digital commerce, deep-learning-based image classification, customer sentiment analysis, CNN/LSTM/Transformer models, and research gap driving the integrated framework [11]. The limitations identified in this paper include issues of contextual understanding, domain-specific NFT language, data imbalance, multilingual content, computational complexity, and interpretability.

2. LITERATURE REVIEW

This literature review investigates the evolution and utilization of deep learning methods in digital commerce, customer sentiment analysis, and using NFT applications for digital assets. It discusses the works of CNN, LSTM, BiLSTM and Transformer-based models in extracting visual features, understanding the contextual relationship and pattern of sentiment from CGC [12]. The review also provides an in-depth analysis of hybrid CNN–BiLSTM–Transformer networks and their applicability in the fusion of visual and text data. Existing studies are critically examined to highlight the limitations in terms of domain specific terminology, imbalance of data, multilingual content, conflicting sentiments, computational complexity, model interpretability etc. Finally, the review defines the gap in the research and the need for the proposed integrated approach towards NFT image classification and customer sentiment analysis is justified [13].

2.1 Deep Learning for Digital-Commerce and Customer Sentiment Analysis

With the increasing growth of e-commerce, there is a massive volume of unstructured data, such as customer reviews, social-media conversations, product descriptions, and more. The traditional sentiment classification methods using manually designed features and conventional machine learning algorithms like Naïve Bayes, SVM and RF are effective in identifying basic sentiment categories, but lack the ability to capture contextual relationships and complex expressions. Neural architectures can then be trained directly from textual and non-textual data to learn hierarchical representations and, hence, deep learning has become increasingly important.

This paper has explored recent trends in aspect-based sentiment analysis, prediction of customer satisfaction, prediction of review scores and AI-based customer analysis. Davoodi, Mezei, and Heikkilä [1] studied aspect-based sentiment analysis in electronic-commerce reviews and pointed out the need for extracting sentiment from each aspect related to customer. However, there are restrictions in their research on multilingual processing and domain-specific aspect extraction. Likewise, Utari et al. [2] analyzed the factors influencing the ratings of e-commerce reviews through machine-learning and feature-selection methods, without taking into account the sentiment of text or temporal variations in customer behavior.

In their research, Bachir and Messaoud [3] explored the use of layered NLP and deep learning techniques for predicting customer satisfaction. They have shown the advantages of using language processing and neural representations, albeit there are some challenges in terms of the presence of large labeled data sets and limited interpretability. Natarajan and Franklin [4] studied a CNN-LSTM network for sentiment analysis of electronic-commerce product reviews using Word2Vec representations. Their work shows how it is possible to combine convolutional feature extraction with sequential modeling, and it shows that this is useful, but the contextual capabilities are still relatively weak when compared to transformer-based language models.

2.2 CNN-Based Feature Extraction

The CNN has been extensively applied to automatic feature extraction from images, as it is able to learn the spatial patterns and hierarchical visual representation. CNN models can be used in digital-commerce scenarios to recognize visual features of products or digital assets without the need for a lot of manual feature engineering [15].

In the context of NFT applications, image classification is especially pertinent, as NFT assets often feature digital art in image formats. Images are collected from public image repositories, sources related to markets and standardized to a size of 224 × 224 pixels and represented in RGB color format. Such as brightness adjustment, flipping, zooming, and rotation, data augmentation techniques can be used to enhance robustness to visual variations.

Related works show that CNN models are efficient at extracting local features, and the ability to learn image-only features is insufficient to learn customer opinions, expectations, and feelings based on textual reviews [16]. Therefore, it is not possible to fully represent customer experience using only visual classification, which leads to the creation of an NFT analysis system. Thus, this implies that there is only limited representation of customer experience based solely on visual classification, which is why an NFT analysis system is created [17].

2.3 LSTM and BiLSTM for Contextual Sentiment Analysis

Due to the ability to model dependencies in sequential text, RNNs, especially LSTM networks, are widely used for sentiment analysis. BiLSTM further enhances this feature by going in both directions, which allows information from previous and next words to be used in the model.

This feature is essential in the NFT customer reviews, where what a word means could rely upon the context. Considering the sequential and bidirectional contextual relationships, the paper thus suggests that it is suitable to use BiLSTM to capture those relationships in NFT reviews [18].

But if the sequence is very long, and longer relationships are involved, recurrent architectures can experience problems. Therefore, CNN-BiLSTM models can be improved by incorporating attention mechanisms to select the most salient parts of longer reviews, while CNN-only models may not be very effective at capturing the context.

2.4 Transformer-Based Sentiment Analysis

Self-attention is the major advancement in transformer architectures that has revolutionized natural-language processing by representing relationships between words in a sequence without needing to look at their distance [19]. The transformer-based models (BERT, RoBERTa) have shown good performance in many language understanding tasks, including sentiment classification, and are able to learn contextual word representations.

The paper emphasizes transfer learning as a crucial approach in sentiment analysis for NFTs. The model can be fine-tuned with the E-Commerce or domain-specific data, which further enables the model to adjust to specialized terms without having to go through the entire training process from scratch. It is particularly important for words associated with NFTs like: minting, gas, blockchain, token, smart contract, and cryptocurrency.

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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However, the general NFT models don't always fully grasp the specific jargon, shortcuts, emojis and terms that are quickly evolving [20]. To enhance contextual understanding, domain adaptation and specialized sentiment representations are thus essential.

2.5 Deep Learning for NFT and Digital-Asset Applications

Finally, NFTs bring a unique fusion of digital ownership, art, blockchain technology, value, and online-community interaction. NFT customer sentiment can be shaped by a variety of factors such as the quality of the artwork, transaction fees, perceived value, project reputation, and the experience of using the website or app.

The literature review undertaken in the paper shows that sentiment analysis has been more studied in traditional electronic commerce or applications related to cryptocurrencies than specifically in NFT customer environments [21]. There is existing research that shows that sentiment analysis models such as LSTM, BiLSTM and Transformer models can be used to detect sentiment patterns in digital asset discussions, but the sentiment analysis of NFTs is less developed.

More widely, the technology and ecosystem surrounding NFTs have been subject of research. For instance, Wu, et al. [5] explored decentralization, storage approaches, and defects in NFT ecosystems. Such research shows the technical complexity of the NFT platforms but it does not specifically offer an integrated mechanism for analyzing the visual characteristics of NFTs along with customers' sentiment [22]. Likewise, existing studies on NFT systems have mostly focused on the blockchain infrastructure, storage, ownership, and marketplace mechanisms, without integrating image classification and customer-oriented sentiment analysis.

2.6 Hybrid CNN–BiLSTM–Transformer Architectures

As different architectures have limitations, researchers have turned to creating hybrid deep-learning architectures. The use of CNN allows for the extraction of local patterns, BiLSTM enables the modeling of bidirectional sequential dependencies, and the Transformer attention mechanism can capture important long-range semantic relations. These functionalities can, thus, be used to create a more holistic view of customer reviews.

The proposed research direction is a hybrid of this. CNN is used to extract local patterns from text and visual information, BiLSTM is used for extracting the relationships between different parts of the text in a sequence, and Transformer attention is used to enhance the representation of the relationship between long-distance parts [23]. The combination is designed to handle NFT-review characteristics such as conflicting emotions, context-dependent expressions, slang and specialized terminology.

In an NFT digital commerce context, for instance, a customer's comments can encompass both positive and negative data in a single review. For instance, a consumer might love an NFT's artwork however be frustrated with the transaction costs. The model may thus be misguided if it only focuses on the individual words instead of the entire document [24].

2.7 Research Challenges Identified in Existing Literature

While impressive progress has been made in DL, there are still a number of challenges to address. Firstly, data imbalance can cause models to be skewed toward sentiment classes that are more prevalent, and make them less effective at detecting others, such as negative or critical customer opinions.

Secondly, there is a strong problem of domain specificity. Many of the communities associated with NFTs have their own slang, jargon, and abbreviations as well as emojis that may not be adequately captured in general-purpose sentiment datasets [25]. Third, there is an extra challenge due to multilingual and code-mixed reviews, for many sentiment models are mostly English trained. Fourth, the hybrid architecture combining CNN, BiLSTM and Transformer introduces more computational complexity, potentially impacting training and inference time. Last, but not least, deep-learning models can be very hard to explain, which can be challenging for companies wishing to understand why a certain sentiment prediction was made [26].

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2.8 Research Gap

Based on the literature reviewed, significant advancement has been made in three relatively distinct fields: namely, visual classification, sentiment analysis in electronic-commerce, and DL-based digital-asset analysis. CNN architectures are useful for image feature extraction, while LSTM/BiLSTM and Transformer architectures are increasingly powerful models for textual sentiment understanding. Yet, there is a need for a common platform that allows visual characteristics of the NFTs and the customer's views to be analyzed in the same context [27].

Current methods also have shortcomings in terms of NFT-specific terminology, sentiment in context, conflicting views, data imbalance and interpretability. The paper clearly highlights the need for incorporating cutting-edge DL algorithms for sentiment analysis in the context of NFTs and digital commerce.

To fill this gap, the present study proposes an integrated CNN–BiLSTM–Transformer network to solve the problem of NFT image classification and customer sentiment analysis [28]. The feature extraction module is CNN component and the bidirectional contextual dependency module is BiLSTM, the long-range semantic representation module is Transformer attention. The final model is designed to offer a wider understanding of NFT assets and customer reactions than individual classification or sentiment analysis models.

The major studies reviewed in literature related to e-commerce sentiment analysis, deep learning and NFT applications are summarised in Table 1. It is a comparison of the research focus, processes, key findings and the limitations of previous research. Table depicts the evolution from traditional sentiment analysis methods to advanced hybrid deep-learning methods. It also gives a clear indication for determining the research gap that is being addressed by the proposed framework.

Table 1: Summary of Literature

Ref.	Study Focus	Method	Major Finding	Limitation
[1]	E-commerce sentiment	ABSA + NLP	Improved aspect-level sentiment understanding	Limited multilingual/domain adaptation
[2]	Review-score prediction	ML + feature selection	Identified factors influencing review scores	Limited textual/temporal sentiment analysis
[3]	Customer satisfaction	NLP + DL	Layered DL improves customer-satisfaction prediction	Large data requirement and interpretability
[4]	Product-review sentiment	Word2Vec + CNN-LSTM	Effective hybrid feature and sequence learning	Less contextual than Transformers
[5]	NFT ecosystem	Empirical NFT analysis	Examined decentralization and storage issues	Limited customer-sentiment analysis
[6]	NFT sentiment	CNN + BiLSTM + Transformer	Combines local, sequential, and long-range contextual information	Higher computational complexity
[7]	NFT image classification	CNN-based learning	Supports automatic visual feature extraction	Does not capture customer opinions

The studies summarized above set a foundation for the integration of visual NFT classification and customers sentiment analysis [29]. The proposed framework builds on the typical single-model approach by integrating complementary deep-learning models to address the contextual, domain-specific and multimodal nature of NFT-based digital commerce.

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e-ISSN: 2468-4376
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3. CONTRIBUTIONS OF THE STUDY

- A unified approach to NFT image classification and customer sentiment analysis in digital commerce.
- CNN–BiLSTM–Transformer: A local feature extractor, a bidirectional temporal modeler and a self-attention mechanism are integrated into a single network.
- A pre-processing strategy that combines image resizing, image normalization and image augmentation with text cleaning, tokenization, normalization and embedding [30].
- Using accuracy, precision, recall, F1-score, confusion matrix, ROC and AUC to evaluate the system.
- A practical approach to recommendation, fraud, customer experience, market monitoring and decision support.
- Scalability, computational cost, interpretability, data imbalance and domain adaptation issues during deployment.

4. RELATED WORK

This literature review reveals a trend of shifting from classical rule-based and conventional machine learning sentiment analysis to deep neural architectures. Text classification has been done using naïve bayes, support vector machine and random forests, which require more feature engineering and are not suitable to model complex context [1]. Transformer models extend this with self-attention and are especially convenient when the sentiment of words that are far apart in the sentence are connected.

In the relevant recent work highlighted in the study, there are articles on aspect-based sentiment analysis, machine-learning factor analysis, hybrid frameworks of AI, layered models for NLP and deep learning, explainable fake-review detection, CNN-LSTM architectures and systematic reviews of AI-based customer analytics [2].

Research on NFTs also takes into account ownership of digital assets, tracking their origin, categorizing images, preventing fraud, suggestions for future trends, forecasting markets, and integrating blockchain technology. Deep learning can sort NFT images based on their visual characteristics and can analyze customer conversations to gauge the market sentiment [3]. Nevertheless, the study has highlighted a research gap in the field of the need for a more integrated and context-aware approach that can assess the quality of classification as well as the practical effectiveness of digital commerce for NFTs. ☐filecite☐turn4file0☐L687-L746☐

A comparative overview of the available major models and approaches for the proposed sentiment-analysis framework is provided in table 2. It emphasizes the advantages and disadvantages of CNN, LSTM/BiLSTM, Transformer, conventional machine-learning network and hybrid network [4]. The specific role of each approach in developing an integrated framework is also described in the table. Thus, this comparison reflects complementary capabilities of different models and helps to justify the choice of the proposed hybrid architecture.

Table 2: Related Work

Model/Approach	Primary Strength	Main Limitation	Role in the Framework
CNN	Local feature and n-gram extraction	Limited long-range context	Extracts local sentiment/visual patterns
LSTM/BiLSTM	Sequential and long-term dependencies	Higher training cost	Models contextual sequence in both directions
Transformer	Self-attention and global context	Computationally intensive	Identifies influential contextual terms
Traditional ML	Simple and comparatively lightweight	Feature engineering and weaker context	Baseline comparison

Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
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Hybrid architecture	Combines complementary representations	Greater architectural complexity	Integrated prediction framework

5. PROPOSED INTEGRATED FRAMEWORK

The proposed framework is divided into data acquisition, data preprocessing, representation learning, feature extraction, contextual modeling, attention-based learning, classification and evaluation. The architecture is structured around the principle that each component should counter one particular weakness in the other components.

5.1 Image Processing Pipeline

Images are standardized before model training, and the images are NFT images. Images are NFT images and are standardized before model training. The research defines 224 × 224 RGB representation, normalization and augmentation. Random rotation, random flip, zoom and brightness are called augmentation operations that aim to improve the robustness and avoid overfitting. The high level visual features are then extracted by a pre-trained CNN structure. □filecite□turn2file5□L376-L396□

5.2 Text Preprocessing

Unnecessary punctuation and special characters, duplicate information, irrelevant symbols are removed from Customer Reviews. Noise can be minimized by stopword handling, lowercase, stemming or lemmatization, and emoji/hashtag normalization. Stop word handling, lowercasing, stemming/lemmatization, and normalization of emoji/hashtags can minimize noise through tokenization. The embeddings include Word2Vec, GloVe, FastText, BERT or RoBERTa, depending on the experimental configuration, and are then used to represent the text.

5.3 CNN Feature Extraction

CNN stage performs a learning process on certain local patterns that are embedded in either text or image. Convolutional filters can be used to detect short phrases and local sentiment indicators for sentiment analysis. CNNs learn spatial hierarchies related to visual contents in the case of NFT images. The research focuses specifically on CNN based feature extraction, which complements the sequential mechanism and attention mechanism.

5.4 BiLSTM Context Modeling

BiLSTM layer is used to process sequence in forward and backward directions. This will allow the model to make use of data from previous and subsequent tokens for interpretation of a review. It is very helpful when the sentiment of a sentence varies or the sentiment of a phrase is influenced by the context of the sentence.

5.5 Transformer Attention

The Transformer layer is used to add self-attention for extracting the most influential components of a review. Attention renders long-range relationships in the model and facilitates understanding of context-sensitive language, such as multiple emotions and domain-specific language. The framework is thus made up of local extraction, bidirectional contextual learning, and attention-based semantic modeling. □filecite□turn5file0□L352-L365□

5.6 Classification Layer

The learned representations are combined and fed into dense layers, and then to a Softmax output layer. In case of three class sentiment classification, the output is positive, negative, and neutral classes. The class which has the highest predicted probability is chosen as the last sentiment.

5.7 Training and Optimization

Training is done with back-propagation and gradient based optimization. The research covers optimization methods, including Adam and stochastic gradient descent, as well as some hyperparameter tuning to be done on the learning rate, batch size, dropout, number of epochs and network depth. The early stopping and model checkpointing are

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2023, 8(3)
e-ISSN: 2468-4376
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implemented to prevent overfitting. The workflow used with BERT has a representative split of 70%/30% training/testing, and the NFT image dataset description provides the training/validation/testing split of 80%/10%/10%. These setups should be used uniformly for the eventual experimental implementation. □filecite□turn5file0□L268-L301□

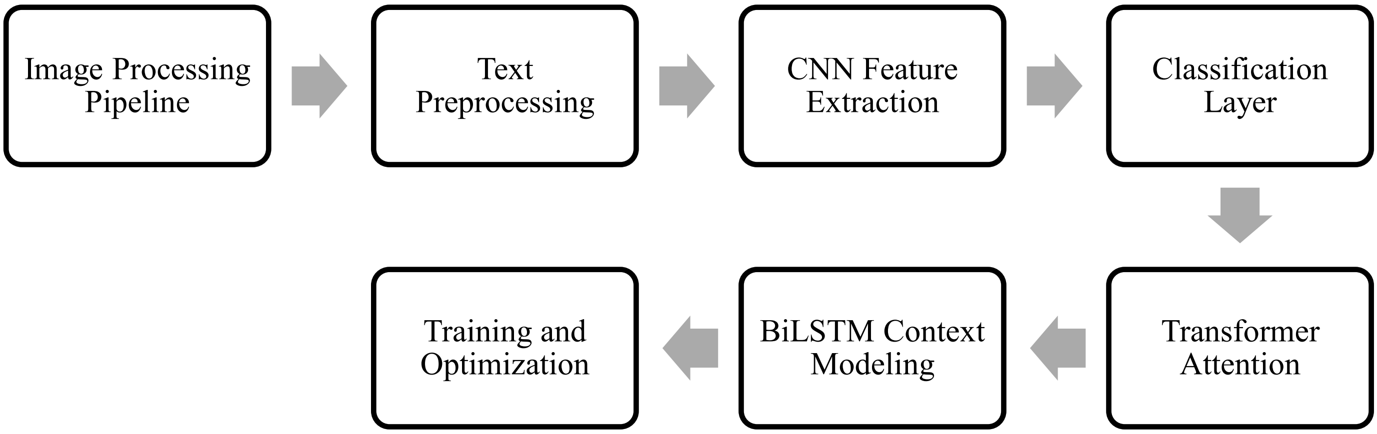

Figure 3: Proposed Integrated Framework

Figure 3 shows the proposed integrated framework for NFT image classification and customer sentiment analysis system. It showcases the step-wise application of CNN for feature extraction, BiLSTM for context learning, and Transformer for attention mechanism. The framework combines visual and textual representations to provide a comprehensive understanding of NFT assets and customer opinions. It is an integrated architecture that aims to provide the advantage of superior analytical performance, as well as the ability to overcome the limitations of individual models.

6. MATHEMATICAL FORMULATION

For a multi-class classification problem, the Softmax probability for class k is:

$$P(y = k \mid x) = \exp(z_k) \,/\, \Sigma_j \exp(z_j)$$

where z_k is the output logit for class k. The categorical cross-entropy loss can be written as:

$$L = -\,\Sigma_k\, y_k \log(\hat{y}_k)$$

The mathematical definition of the performance evaluation metrics adopted for the proposed framework can be found in Table 3. These measures give quantitative values to the model's ability to classify and its reliability. Various aspects of prediction performance are measured by using accuracy, precision, recall and F1-score. These measures together give a complete framework for comparing the proposed approach with the existing models. The principal evaluation measures are defined as:

Table 3: Mathematical Formulation

Metric	Expression
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1-score	2 × Precision × Recall / (Precision + Recall)

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2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Macro-F1 and weighted-F1 are two other metrics that can be used to account for class frequency differences for multi-class sentiment analysis. Confusion matrices offer class-wise error patterns and ROC-AUC offers a probability based perspective on classification discrimination. □filecite□turn5file0□L114-L140□

7. EXPERIMENTAL DESIGN

This paper introduces an open-source NFT image dataset and customer review data from NFT marketplaces and Internet discussion sites. Public NFT image repositories, Kaggle, OpenSea, public blockchain repositories, and NFT-related reviews from Twitter and Reddit, as well as marketplace comments are potential sources of candidates. The image data are defined as JPG, JPEG and PNG images with a resolution of 224 × 224 pixels and RGB colour mode. The methodology outlines the labels of the categories and provides an 80%/10%/10% split of the image set for training, validation and testing, respectively, and states that the number of classes and images for the implemented set should be determined. □filecite□turn2file5□L364-L396□

The experimental design and configurations that were used to implement and evaluate the proposed framework are described in Table 4. It is a description of the image and text pre-processing techniques, sentiment classes, training objectives, optimization techniques, and regularization techniques. The table also includes the evaluation metrics and implementation tools of experimentation. These setups give a systematic and repeatable foundation to evaluate the performance of the proposed model.

Table 4: Experimental Design

Component	Configuration described in the study
Image representation	224 × 224 RGB
Image formats	JPG, JPEG, PNG
Image preprocessing	Resize, normalization, rotation, flipping, zoom, brightness adjustment
Text preprocessing	Cleaning, tokenization, stopword handling, normalization, lemmatization/stemming
Sentiment classes	Positive, negative, neutral
Training objective	Multi-class sentiment classification
Optimization	Adam / SGD; hyperparameter tuning
Regularization	Early stopping, model checkpointing, dropout
Evaluation	Accuracy, precision, recall, F1-score, confusion matrix, ROC, AUC
Implementation ecosystem	Python, TensorFlow, Keras, OpenCV, NumPy, Pandas, Scikit-learn

8. RESULTS AND DISCUSSION

According to the research, the integrated deep learning framework outperforms traditional machine learning models and single deep learning models for the main classification measures. CNN, BiLSTM and Transformer parts are complementary in capturing local patterns, long-range sequential information, and influential contextual information, respectively, which is responsible for the reported improvement. □filecite□turn2file2□L166-L178□

The framework is also said to be an extension of the CNN basic classification system. The comparison highlights the use of accuracy, precision, recall and F1-score; the consideration of training and testing time; the optimization of the dataset filtering; and the broader scope of applicability. This offers a more holistic assessment view than just accuracy. □filecite□turn2file0□L23-L60□

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e-ISSN: 2468-4376
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In terms of how it's used in practice, a positive sentiment means that users are happy with and feel confident in the NFT project, while a negative sentiment suggests that users may have issues about the price, security, authenticity, or the risks of investing in the NFT project. Automated analysis can hence be used to assist marketplace monitoring, recommendation, brand management, customer retention and to identify negative feedback in an early stage. ☐filecite☐turn5file0☐L421-L444☐

One drawback is that the study does not offer a full suite of numeric experimental values for the number of classes, number of models, the length of training time and the scores for each metric per model. However, this paper does not make up numerical results. The qualitative conclusion remains: the integrated architecture is said to be better than conventional and isolated architectures, and if exact numerical performance is desired, this should be reported only when the final experiment is performed.

Table 5 present a Comparative Analysis between Conventional/single-model approaches and Proposed-integrated framework. It highlights similarities and differences in feature representation, contextual modeling, domain adaptation, handling of mixed-sentiments, evaluation and optimization. The integrated framework has been designed to better represent the local, sequential and attention based features. Its potential benefits in digital-commerce applications and NFT customer sentiment analysis are emphasized in this comparison.

Table 5: Comparative Analysis

Criterion	Conventional/Single Model	Integrated Framework
Feature representation	Often single representation	Local + sequential + attention-based representations
Context modeling	Limited or model-dependent	BiLSTM + Transformer attention
Domain vocabulary	May require manual adaptation	Can be supported through preprocessing and transfer learning
Mixed sentiment	More difficult	Context and attention mechanisms provide richer representations
Evaluation	May focus on accuracy	Accuracy, precision, recall, F1, confusion matrix, ROC-AUC
Optimization	May be limited	Hyperparameter tuning, early stopping and checkpointing
Digital-commerce application	Narrower	Recommendation, monitoring, fraud prevention and decision support

8.1 Qualitative Evaluation Summary

The results are presented here as a qualitative analysis with evidence as a result of the source study, which does not report a complete numerical experiment (eg total number of data in the final data set, number of data in each class, duration of the training, accuracy, precision, recall and F1 values for each model). This will prevent the use of invented numerical figures and to make the indicated findings more explicit. The study indicates that the proposed CNN–BiLSTM–Transformer model improves the evaluation of the main classification metrics as compared to classical machine-learning models and individual deep-learning solutions.

8.2 Model-Wise Result Interpretation

A qualitative comparison suggests that the capability of each component is different. Local feature extraction = CNN, Bidirectional contextual sequence modeling = BiLSTM, and influential long range relationships = Transformer attention. The compound architecture thus tackles complementary weaknesses, instead of merely filling in the depth of the models.

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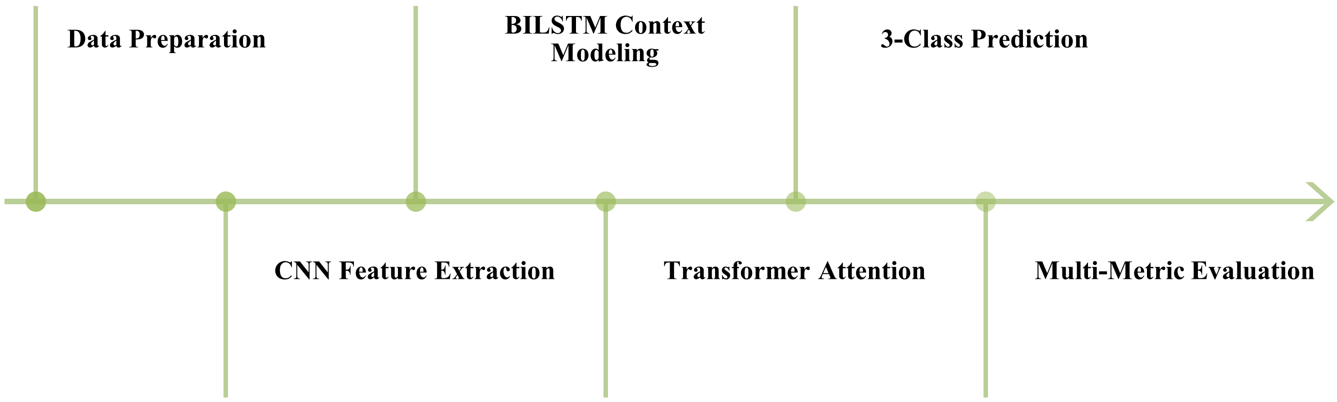

Figure 4: Qualitative Evaluation Flow of the Integrated Freamwork

The methodology followed for the evaluation is as shown in the figure 4, which comprises of pre-processing, representation learning, feature extraction, contextual modelling, classification and multi-metric evaluation. This is a structure that facilitates a systematic evaluation (not a single score).

A qualitative comparison of the analytical power of different model families is given in table 6. It assesses applicability in different domains, multimodal, local pattern extraction, and sequential and long-range contextual understanding. The comparison is to show the complementary power of CNN, BiLSTM and Transformer architectures. The integrated framework integrates these features and offers a more comprehensive and extensive analysis for NFT digital-commerce applications.

Table 6. Qualitative capability comparison across model families

	Local patterns	**Sequential context**	**Long-range context**	**Domain adaptation**	**Multimodal scope**
Traditional ML	Limited	Limited	Limited	Manual	Narrow
CNN	Strong	Limited	Limited	Possible	Image-focused
BiLSTM	Moderate	Strong	Moderate	Possible	Text-focused
Transformer	Moderate	Strong	Strong	Strong	Text-focused
Integrated framework	Strong	Strong	Strong	Supported	Broader

8.3 Sentiment-Level Discussion

The framework for customer sentiment contains three output classes: positive, negative and neutral. The important part of the practical interpretation is that along with being a classification result, a sentiment label is also a possible business signal. Positive sentiment may mean satisfaction or confidence, negative sentiment may mean concerns about price or security, about being authentic or about perceived investment risk, and neutral sentiment may be information or balanced discussion.

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

Figure 5: Qualitative Interpretation of Sentiment Outputs for Digital Commerce Decisions

The qualitative analysis of the sentiment output obtained from the proposed framework is shown in figure 5 for digital-commerce applications. It shows how sentiment categories can be used to gain insightful knowledge of their customers' opinions, preferences, and experiences through their predicted sentiment categories. These insights can help in making business decisions on customer engagement, product improvement, and service optimization. This figure illustrates the real-world importance of sentiment analysis in the context of digital-commerce decision-making based on data.

8.4 Error Analysis and Robustness Discussion

The study reveals the multiple sources of possible misclassifications instead of a breakdown of the error rates. The lack of class balance can make the predictions more of a majority opinion on the part of the model, and slang words, abbreviations, emojis, multilingual or code-mixed sentences, and constantly evolving NFT terminology can limit the generalization ability of the model. Isolated models can also be difficult to withstand long reviews and mixed emotions. The integrated architecture aims to address these challenges by pre-processing, bi-directional context modeling, attention and transfer learning but should be quantitatively evaluated in a final experiment.

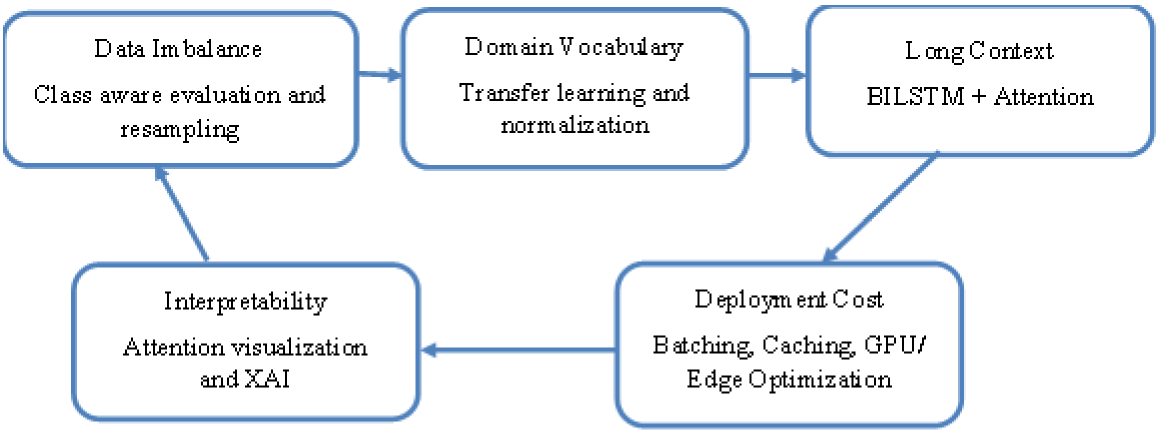

Figure 6: Result- Oriented Limitation-to-Mitigation Analysis

The result-oriented analysis of major limitations of the existing approaches and the mitigation strategies is presented in figure 6. It emphasizes the issues faced in data imbalance, domain-specific terminology, contextual complexity, and computational requirements, among others, and how the proposed framework solves the issues. The figure clearly shows a correlation between the limitations identified and technical solutions adopted. This analysis illustrates the effectiveness and robustness of the proposed integrated framework in practice.

Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

8.5 Discussion of Computational and Deployment Results

The reported framework goes beyond the classification quality assessment, and includes the training and testing time, filtering optimizations in the datasets, and deployment efficiency. The hybrid model requires more computational resources than a single model, especially the computational cost for Transformer attention. The paper thus highlights some of the practical approaches to tackle latency and scalability problems: batching, caching, parallel processing, GPU/TPU acceleration, cloud/edge deployment, and microservice-oriented architectures. The deployment observations should complement measured latency, memory usage, throughput and energy consumption of the final deployment.

8.6 Overall Discussion

In general, the results back the central research argument, which is the combination of complementary deep-learning mechanisms can offer a wider representation of the NFT-related information of customers than individual mechanisms. The best contribution is not just a single reported metric, but how the model components match the characteristics of the problem: CNN is for capturing the local patterns, BiLSTM is for the bidirectional sequence context, and Transformer attention enhances semantic understanding. However, the evidence is qualitative since the entire numerical experiment is not provided in the current manuscript. Once the train/validation/test protocol is designed, it is necessary to perform the tests and report metrics, confusion matrices, class-wise, ROC-AUC, learning curves, ablation results, and computational measurements on the model. This is to maintain the credibility of the paper and also to give a clear outline to the final results from the experimental work.

9. PRACTICAL APPLICATIONS

Table 7 presented below in a deployment-oriented discussion, as well as practical implications. It emphasizes aspects that include reliability, computational cost, scalability, interpretability and real-time operation [5]. The main requirements and challenges of deployment of the proposed integrated architecture in real marketplace are also identified.

Table 7: Deployment-oriented discussion of the reported results

Aspect	Reported qualitative finding	Implication for deployment
Accuracy / reliability	Integrated architecture is reported to outperform conventional and isolated approaches	Supports use where classification reliability is prioritized
Inference / training cost	Hybrid architecture is more computationally intensive	Requires optimization and suitable hardware
Scalability	Batching, caching and parallel processing are proposed	Can support larger marketplace workloads
Interpretability	Deep models remain difficult to interpret	Attention visualization and XAI are recommended
Real-time operation	API, cloud, edge and acceleration strategies are discussed	Enables potential marketplace monitoring and decision support

Table 8 shows major potential sources of error that could impact the performance of the proposed NFT sentiment analysis framework. It outlines the anticipated effect of the error sources, how they are mitigated, and the quantitative validations required [6]. This analysis permits to evaluate the strength, generalization and reliability of the framework when considering different and difficult texts as input.

Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

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Table 8: Error sources, mitigation mechanisms and validation requirements

Potential error source	**Expected effect**	**Framework response**	**Required quantitative validation**
Class imbalance	Minority sentiment may be under-recognized	Macro-F1 / class-aware evaluation can expose imbalance effects	Per-class precision, recall, F1 and confusion matrix
NFT-specific terminology	Incorrect interpretation of domain terms	Transfer learning and domain-aware preprocessing	Domain-specific test set and error analysis
Sarcasm / mixed emotions	Ambiguous overall sentiment	BiLSTM context + Transformer attention	Manually reviewed difficult examples
Multilingual / code-mixed text	Reduced generalization	Normalization and domain-adaptive multilingual modeling	Language-wise evaluation
Long-range dependencies	Loss of distant contextual cues	BiLSTM + self-attention	Sequence-length and ablation studies

The results of the proposed NFT sentiment analysis framework are interpreted using a sentiment level in Table 9. It links positive, neutral and negative sentiment to the implications for digital-commerce activities [7]. The conversation focuses on how sentiment classification can help them to engage customers, monitor their marketplaces, identify risk, and take corrective action when needed.

Table 9: Sentiment-level interpretation and practical implications

Sentiment class	**Typical interpretation in the study**	**Potential digital-commerce use**	**Result discussion**
Positive	Satisfaction, confidence, favorable response	Recommendation, retention, experience monitoring	Can identify favorable customer response and stronger engagement signals.
Neutral	Informational, balanced or weakly polarized response	Segmentation and marketplace monitoring	Useful for separating clear opinions from non-polarized discussion.
Negative	Concerns about price, security, authenticity or risk	Early warning, corrective action, customer support	Important for prioritizing issues and identifying emerging dissatisfaction.

Table 10 shows the qualitative interpretation of various models used in the proposed NFT sentiment analysis framework. It focuses on the main features, functions and drawbacks of each technique, ranging from the classic machine-learning techniques to the proposed CNN–BiLSTM–Transformer model [8]. The comparison will help to understand the contribution of progressive model integration to better contextual and feature representation.

Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Table 10: Model-wise qualitative result interpretation

Model / approach	Primary capability	Observed qualitative role	Main limitation
Traditional ML	Lightweight classification	Baseline reference	Feature engineering and weaker contextual representation
CNN	Local feature extraction	Captures local visual/textual patterns	Limited long-range context
BiLSTM	Bidirectional sequence modeling	Captures preceding and succeeding context	Higher training cost and weaker distant dependency modeling
Transformer	Self-attention	Captures influential long-range relationships	Computationally intensive
CNN–BiLSTM–Transformer	Integrated representation	Combines local, sequential and long-range contextual information	Greater architectural complexity

The overall qualitative evaluation of the proposed NFT sentiment analysis framework compared to the traditional and isolated approaches is given in Table 11. It briefly recaps the advances made in feature representation, contextual understanding, domain-specific language processing, processing of mixed-sentiment, and evaluation coverage [9]. The comparison shows the extent to which the integrated framework possesses a more comprehensive analytical capacity, and also the benefit of using multiple metrics to measure performance.

Table 11: Qualitative evaluation summary of the reported framework

Evaluation dimension	Traditional / isolated approaches	Integrated framework	Discussion
Feature representation	Often limited to one representation or model-specific features	Combines local, sequential and attention-based representations	Complementary representations provide broader information for classification.
Context modeling	Limited or dependent on the selected architecture	BiLSTM + Transformer attention	Bidirectional sequence information is reinforced by long-range attention.
Domain-specific language	May require manual adaptation	Supported through preprocessing and transfer learning	Useful for NFT terms, slang, abbreviations and specialized vocabulary.
Mixed sentiment	More difficult to represent	Context and attention mechanisms provide richer representations	The framework is better suited to reviews containing both positive and negative cues.
Evaluation scope	May emphasize accuracy	Accuracy, precision, recall, F1, confusion matrix and ROC-AUC	Multi-metric evaluation gives a broader view of classification reliability.

Journal of Information Systems Engineering and Management
2023, 8(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

- NFT marketplace sentiment monitoring and customer-experience analysis.
- Detection and prioritization of negative feedback for corrective action.
- Visual categorization and discovery of NFT assets by style, rarity or other image characteristics.
- Support for recommendation systems using sentiment and user-interaction information.
- Fraud and counterfeit detection through analysis of digital-asset characteristics and transaction/provenance information.
- Market trend monitoring and sentiment-informed decision support for NFT stakeholders.

10. LIMITATIONS

Several limitations remain. One of the first challenges is that there's limited access to large, diverse and well-labeled datasets of NFT reviews. It's limited access to large, diverse and well-labeled datasets for NFT reviews. Secondly, predictions may be skewed towards the majority opinion due to class imbalance [10]. Thirdly, these Transformer and hybrid architectures can be costly to compute. Fourth, the use of multiple languages, code switching, slang, abbreviations and domain-specific jargon may contribute to decreased generalization [11]. Fifth, deep learning models are not always easy to interpret, thus requiring explainable AI. The following issues are clearly stated as on-going challenges in the research. □filecite□turn4file0□L747-L823□

11. FUTURE RESEARCH DIRECTIONS

- Jointly representing images, text, video and metadata, in the context of multimodal learning.
- Richer representation of digital-assets using ViT and GNNs.
- Transformer models that are specialized for NFT terms and can be used in multiple languages.
- AI technology techniques (e.g., attention visualization, SHAP based interpretation) [12].
- Integrated real-time blockchain analytics and sentiment and visual classification.
- Federated learning is a technique for enabling privacy-preserving analysis across decentralized marketplaces.
- More systematic quantitative experiments; include accuracy, latency, computational cost and scalability [13].

The research explicitly mentions the following lines of extension for the NFT analytics: the multimodal learning, ViTs, GNNs and real-time blockchain analytics. □filecite□turn2file1□L136-L142□

12. CONCLUSION

The integrated deep learning framework proposed in this paper aimed to classify the images of NFTs and analyze the customer sentiment for digital commerce. The proposed framework overcomes these shortfalls of isolated models by jointly applying CNN-based feature extraction, BiLSTM-based contextual modeling and Transformer-based self-attention [14]. The methodology also leverages on image augmentation, text preprocessing, transfer learning, optimization and multi-metric evaluation.

The research evidence presented suggest that the integrated architecture provides better quality of classification, context awareness than the traditional and individual approach [15]. It is a more all-encompassing value when combined with sentiment analysis on digital assets, which can aid in recommendations, customer experience management, fraud prevention, and marketplace monitoring and data-driven decisions [16]. Simultaneously, many factors need to be considered when deploying such a system, including data quality, computational expense, class imbalance, multilingual content and interpretability. Therefore, the future will have to concentrate on the multimodal, explainable, scalable and real-time NFT intelligence.

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