

Deep Learning Framework for Intellectual Property Authentication of Digital Artworks

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Abstract: The fast growth of production and dissemination of digital art via websites and artificial intelligence technology has posed serious issues in the field of protecting intellectual property and authentication verification. Current methods sometimes have difficulty telling actual artworks apart from real derivative works and copyright-infringing material, especially with complex digital adjustments or AI-generated changes. This research work aims to propose an intelligent framework for the verification and copyright protection of digital artwork. The proposed framework combines deep feature extraction, semantics graph construction, a Graph-Manifold invariant representational learning and classification based on machine learning to accurately classify original, derivative and infringing artworks. The proposed framework includes of several sequential stages such as image preprocessing and normalization, salient region detection, a deep the extraction of features, semantic graph structure, Graph-Manifold based invariant feature learning, feature similarity measurement performed by cosine similarity and final classification by Support Vector Machine (SVM). The benchmark dataset consisted of 9,000 digital artworks comprising original artworks, lawful derivatives and copyright infringing pictures acquired via sophisticated modification and AI based approaches. The experimental results showed that the suggested framework performed better than the current techniques. The semantic Graph-Manifold framework achieved a general accuracy in classification of 98.1%, F1 score of 0.967 and AUC value of 0.982. Unaffected by image edits, stylistic shifts, or AI-generated adjustments, the system could distinguish between legitimate derivative works and those that infringed on copyrights. Semantic graphing, graph-based representational learning, and support vector machine classification all work together to provide a solid strategy for ensuring the legitimacy of digital artworks and safeguarding intellectual property. In modern AI-driven creative environments, the proposed approach offers a practical answer to the problems of copyright management and through the internet asset protection while simultaneously improving semantic understanding, classification accuracy, and misclassification rates.

Keywords: Deep Learning, Visual Similarity Detection, Graph-Manifold Learning, Digital Copyright Protection, Semantic Graphs, Support Vector Machine, Artificial Intelligence Generated Art.

1. Introduction

The last few decades have seen rapid advancements in digital artwork technology and computational and artificial intelligence-driven artistic media. This has resulted in an unprecedented expansion in the creation and distribution of digital art artworks throughout digital platforms, virtual reality virtual worlds, and non-fungible tokens (NFT) markets. Such digitization has transformed the idea of creative intellectual property and made digital works more susceptible to unauthorized copying, re-editing, intelligent copying and deep-generative plagiarism. This has led to severe legal and technological problems around authenticating and safeguarding digital the copyright [1][2]. With the rise of computational AI tools that can generate visual artwork that mimics the original artistic style with high fidelity and similarity, authenticity of digitally created artwork is a major concern in cybersecurity, proprietary protection, and digital media analysis. Despite the large advances in recognition of images and visual classification, conventional systems could not differentiate the original works from the valid derivatives or intellectual property infringers due to the structural and semantical complexity of modern digital artwork [3].

Most previous counterfeit detection algorithms are based on simple visual criteria such as color, texture, edges or conventional image matching methods. These approaches, however, are frequently inefficient for complex modifications such as stylistic changes, reconstructions, or neural network creation. In addition, the use of local characteristics alone results in a loss of deep semantics and structural linkages between parts of an artwork, which degrades the capacity of the system to produce the right and accurate classifications [4]. To get around these problems, researchers have been combining deep learning with semantics graph modelling to create better representations that can understand the complex relationships in digital images. In order to increase analytical accuracy and intelligent conclusions, the semantic network allows for the full expression of the relationship between creative components, composition patterns, and visual characteristics [5]. also found that deep graph learning models, also known as Graph Neural Networks, outperformed traditional models when it came to identifying invariant characteristics and analysing intricate structural relationships in very complex data [6]. Despite significant advancements in this field, several important research challenges remain, most notably:

- The challenge of identifying works that were influenced by others yet underwent significant stylistic modifications.
- When it comes to recording the semantic links between creative aspects, traditional methods have their limits.
- The very great visual likeness between the original and the AI-generated works.
- The necessity for models that provide accurate categorisation judgements with quantitative confidence ratings.
- The lack of interpretability of many modern deep learning models.

In view of these issues, this research provides an integrated intelligent system to authenticate the validity of the digital artworks. This framework is comprised of methods such as the extraction of features, semantic graph creation and graph-manifold continuous learning, and also a supporting vector machine (SVM) method that is used to boost the accuracy of classification and decision making. The system starts by preprocessing and normalizing to enhance the quality of the digital data, then it identifies the salient areas and extracts the deep features. Finally, it builds a semantic graph representing the relations between the visual parts in the artwork. Graph learning methods are then used to derive stable and inviolable representations robust to different digital changes and alterations. The contribution of this work is Scientific value is that it suggested an enhanced model which integrated structural and semantic evaluation with deep learning in a single structure for verification of digital copyrights. The reliability of technological systems used for documentation is enhanced, and the rates of misclassification are decreased, as a result. Digital creative asset management, electronic material monitoring, and intellectual property protection in a future reliant on generative artificial intelligence are all areas that benefit greatly from the study.

The rest of the research paper was divided as follows: Section 2 explains how this approach has gained increasing attention in the fields of digital artwork documentation, digital copyright security, and the assessment of visual similarities or plagiarism. Section 3 presents research to illustrate the structure of the proposed system using a technical and digital analytical sequence, followed by its refinement and processing. Section 4 describes the pilot setup, including datasets, setup techniques, training settings, and evaluation metrics. The proposed methodology is then evaluated for documenting digital artwork using a copyright infringement criteria database created using advanced AI-based pattern processing and transfer techniques. Section 5 describes the experimental results and discussion, covering classification performance, curve analysis, confusion matrix evaluation, exclusion studies, and comparative performance evaluation to determine the relative importance of each component of the proposed system. Section 6 concludes the work and suggests recommendations for further research, demonstrating that this research is an effective means of protecting intellectual property and offers high flexibility in the face of various types of digital updates and in verifying the legitimacy of digital artworks.

2. Related works

Three primary areas have recently received attention in the field of digital artwork authentication: (1) digital copyright security using fingerprints, watermarks that are or deep models; (2) visual similarities or plagiarism assessment; and (3) detection of AI-generated works.

Finding human-and AI-made artworks that are easily distinguishable was the subject of research by according to [7] applying CNN, SVM, and MLP, among other machine learning and deep learning techniques, the research analyzed intricate art genres including Expressionism, Cubism, and Baroque. The findings demonstrated that the deep models were able to obtain excellent performance in binary classification of human vs AI made art. However, the research was still confined to the coarse categorisation of “human” and “AI-generated” and could not sufficiently address the issue of works which are derivative or partly comparable to original works. Another study by [8] proposed a multi-level framework for visual plagiarism detection in design by combining generic conceptual representations with specific visual cues and field knowledge in similarity detection. The novelty of this research was the use of not just direct visual similarities, but also the effort to associate the global meaning of the picture with its particular features. But the main concern was on poster design, which was not a full semantic graphical model that could express the structural links between picture parts and their artistic aspects.

In another aspect, [9] studied watermarking strategies in latent diffusion models and emphasized that the fast growth of image generating models has raised the need for source tracking and copyright protection methods. The study described that watermarking in latent space could be a promising way to trace generated images, but it is often still coupled to the generating stage itself and may be insufficient for digital works which have been edited, transformed, or generated by an original work with or without a clear watermark. The research by [10] also shown that the AI-generated picture detection systems, particularly those according to watermarking, could be susceptible to malicious assaults and small alterations that enable the evasion of detection measures. This result implies that the use of just watermarks is not enough to develop a strong identification system, it requires a more profound visual and semantic evaluation to withstand digital tampering.

In [11] proposed a digital picture copyright protection and management approach based on artificial intelligence and blockchain technology. The research was based on rights registration, a digital fingerprints storage, and the enhancement of detection of picture authenticity using a deep model, such as MobileNetV2. This study is important because it connections legal and technological protection, but the focus is mainly on the registration and document management, without exploring the semantic and structural connections inside the artwork itself, nor proposing a graph-manifold representation for artistic features. In [12], the paper studies the problem of identifying plagiarism of anime character graphics. The paper suggested a model based on Seq2Seq to extract morphological traits and then utilized the Fréchet distance to quantify the similarity between the original and the imitation version. This research helped to highlight the relevance of formal elements for the detection of plagiarism. However, this study was confined to anime character pictures, which limited its generalizability to other genres of digital art. The study showed that the ability to distinguish between human art and artificial intelligence-generated artwork becomes more challenging with the advancement of modern models that are generative especially in environments with modification or attempts to trick the system, when it comes to detecting machine-generated art. This highlights the importance of algorithms that go beyond the superficial categorisation and depend on invariant characteristics, salient areas and the study of deep semantic linkages.

New study [13] studied the conceptual and applied evolution of graph neural networks, and showed that graph data is especially useful when interactions between components are important for the learning process. This idea is useful in the area of digital art in that a piece of art is not constituted merely of discrete components but of interactions between forms, colours, important areas and

compositional patterns. However, there are still few studies that explicitly use GNN to verify digital art and identify infringement. Current legal studies reveal that generative AI has posed significant issues to the rules of intellectual property, notably since copyrighted artwork is utilised for training and when models generate visuals similar to the original work. [14] identified significant gaps in the current legal frameworks on AI-generated material, and the RAND study (2024) suggested that the concerns of statutory protection, training using copyrighted works and the outputs of standard generative models are still under controversy.

Finally, a survey of prior work finds that the majority of study has focused on either the detection of AI-generated pictures, or watermarks, or evaluating direct visual similarity. However, these techniques are essential, but they still face numerous scientific constraints, the most prominent of which is the difficulty in discriminating between original work and valid derivative work and copyright violation, particularly when the alterations are subtle and implicit. The main research gap lies in the lack of an integrated framework that combines: revealing prominent regions, extracting deep features, constructing a semantic graph, learning unaltered graph-manifold representations, and then making a classification decision supported by confidence scores and similarity rankings. Therefore, the current research addresses this gap by proposing an intelligent model capable of visually analyzing digital artwork.

3. Proposed System

The proposed system is based on an analytical sequence that begins with the input of the digital artwork, followed by its enhancement and processing. Next, significant regions and deep features are extracted, and a semantic graph is constructed to represent the internal relationships between the components of the artwork. An immutable Graph-Manifold representation capable of withstanding digital modifications is then learned. Finally, a SVM is used to make the final decision, calculating the confidence score and similarity ranking.

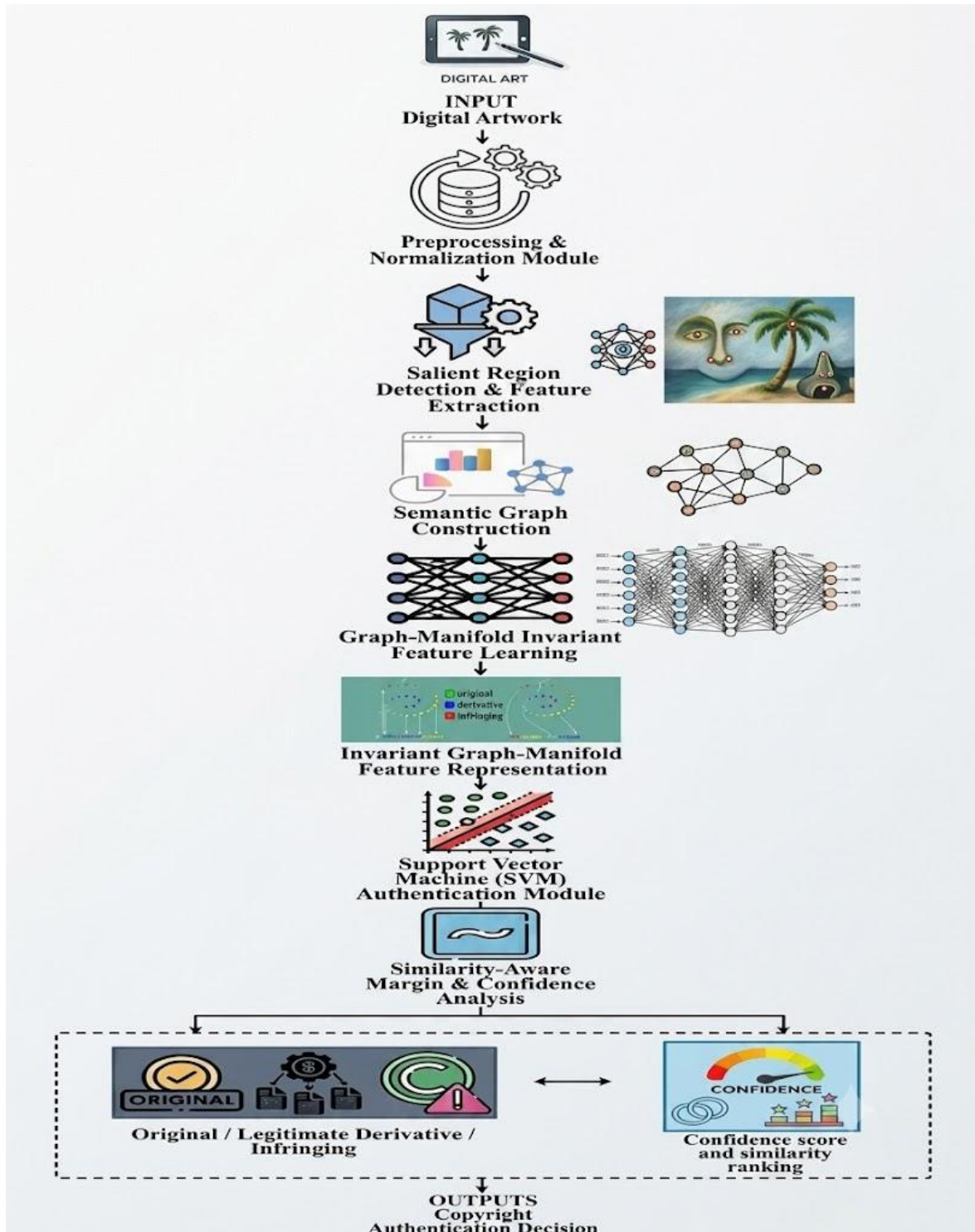


Figure (1): General structure of the proposed system for digital art authentication

This technique tackles a major difficulty in digital protection of copyrights the similarity of artworks cannot be always a surface and easily detectable resemblance, but might be a deeper semantic, artistic or structural one. The suggested approach thus offers a more precise and dependable tool for evaluating the originality associated with digital artworks and identifying any infringements.

3.1 Inputting the digital artwork

The suggested method first imports digitally generated artwork into the analytic environment, represented as a digital multidimensional picture comprising colour and visual information. [16] This input is the main source for all further analysis. The system gets digital photos of different types and sizes. The image is described mathematically by a matrix:

$$I \in R^{H \times W \times C} \quad (1)$$

You can formulate it academically, without repetition, as follows:

The digital picture is the system input, shown as (I). It is a matrix with three dimensions, with dimension ($H \times W \times C$), and is an employee of the set of both real and imaginary values (R). The picture is represented by its height (H), width (W) and number of colour channels values (C). For example, the RGB colour model has three colour channels. This digital construction offers the complete mathematical explanation of the visual and chromatic data of the artwork. This opens the path to further evaluation and feature extraction of the system, which is a key aspect of the authenticity verification and comparison with the reference work from the database.

3.2 Pretreatment and Normalization

After the digital image is input, the data moves to a pre-processing stage, which aims to improve image quality and standardize its characteristics before in-depth analysis begins. This stage includes digital noise removal, contrast enhancement, image resizing, and color normalization to minimize the impact of variations in lighting conditions, resolution, and digital format. Normalization is performed according to the following equation:

$$I_{norm} = \frac{I - \mu}{\sigma} \quad (2)$$

Where:

I represent the original value of each pixel in the image.

μ represents the average color values of all pixels in the image or the dataset.

σ represents the standard deviation of the color values.

I_{norm} represents the normalized value after processing.

This equation is used to center the data around a zero and normalize the fluctuation of the data by removing the average value for every pixel and dividing by the deviation from the mean. This results in positive numbers being above average, and negative values being pixels below average.

This approach helps to lessen the effect of differences of lighting, brightness and contrast across photos taken in various settings and avoids the domination of learning by high numerical values. Thus, all images belong to the statistically converged distribution with the mean close to zero and the standard deviation being close to one, which makes the training process more stable, speeds up the convergence of the model, increases the accuracy of the extraction of visual features and allows to make objective and reliable comparatives between different artworks.

Interpretation of Expected Results After Normalization:

If $I_{norm} = 0$, this means that the pixel value is equal to the image average.

If $I_{norm} > 0$, this means the pixel is brighter than average.

If $I_{norm} < 0$, this means the pixel is dimmer than average.

The higher the absolute value of $inorm$, the greater the deviation of the pixel from average.

This normalization is an important step before to feeding photos to deep learning models as it enhances the learning efficiency and minimizes the classification mistakes due to small differences in shooting settings.

3.3 Identifying prominent areas and extracting features

At this step, the system analyses the digital picture to find the most important and influential regions within the artwork, including edges, stylistic patterns, a compositional one features and unique visual symbols. This approach is based on consideration mapping or deep learning models, which are used to find the key characteristics of the artwork. The prominence of the map is provided as a relation.

$$S(x, y) = F(I_{norm}) \quad (3)$$

Where $S(x, y)$ represents the importance of each point within the image, and (F) is the feature extraction function. After identifying the important regions, the deep features of each region are extracted using:

$$f_i = \phi(R_i) \quad (4)$$

Where R_i represents the prominent part of the image, and f_i is the vector of extracted features. This stage allows the system to focus on the intrinsic technical characteristics rather than relying solely on the surface appearance of the image.[18]

3.4 Semantic Graph Construction

After extracting visual features from different areas within the artwork in the previous phases, the system moves to a more advanced stage: constructing a semantic graph. This graph aims to represent the structural and semantic relationships between the various elements within the image. This phase is fundamental to the automated understanding of artworks because it not only focuses on studying individual elements but also analyzes how these elements relate to one another within the artwork. [19]

In this phase, the artwork is represented as a mathematical graph that defines the relationship:

$$G = (V, E) \quad (5)$$

Where (V) represents the set of nodes, and (E) represents the set of relationships between the nodes. The strength of the relationship between any two nodes is calculated using the similarity equation.[19][20]

$$A_{ij} = \exp\left(\frac{\|f_i - f_j\|^2}{2\sigma^2}\right) \quad (6)$$

Where:

A_{ij} represents the weight of the relationship or degree of similarity between nodes i and j .

(f_i) represents the feature vector of the first node.

(f_j) represents the feature vector of the second node.

$\|f_i - f_j\|^2$ represents the square of the Euclidean distance between the two feature vectors.

(σ) represents the bandwidth parameter, which controls the sensitivity of the similarity.

(\exp) is the exponential function used to convert the distance into a similarity value, typically between 0 and 1.

This equation is based on the principle that visually or semantically similar elements should have stronger relationships within the graph. When the features of two nodes are very close, the distance between them becomes small, and therefore the value of A_{ij} approaches 1, indicating a strong relationship between them. Conversely, when the features are very different, the distance increases, and the value of A_{ij} approaches zero, indicating a weak relationship between the two nodes.

3.5 Learning Invariant Features Using Graph-Manifold

This step is the intellectual core of the suggested system where the generation of unchanging and stable representations for digital artworks is done by deep graph learning methods. The purpose of this step is to make the system able to recognise the artwork even though it has been altered—for instance, rotated, cropped, colored, or reutilized. The node illustration is updated using the equation. [21]

$$h_i^{(l+1)} = \sigma \left(\sum_{j \in N(i)} A_{ij} W^{(l)} h_j^{(l)} \right) \quad (7)$$

where $h_j^{(l)}$ is the node representation used in the present moment layer, and $W^{(l)}$ is the learned weights matrix. A full depiction of the work of art is developed by going through multiple levels of learning:

$$Z = Pool(h_1, h_2, \dots, h_n) \quad (8)$$

This final representation expresses the complete semantic and stylistic structure of the artwork.

3.6 Invariant Feature Representation and Similarity Measurement

After the graphical learning process is complete and the semantic and structural relationships between the elements of the artwork are extracted, the deep learning network produces a final representation vector, denoted as Z . This vector contains high-level information describing the distinctive characteristics of the artwork, including its artistic style, visual composition, spatial and semantic relationships between different elements, and the artistic patterns the model learned during training.

When examining a new artwork, its representation vector, denoted Z_q , is first extracted and then compared with the stored vectors of reference works within the database, each denoted by Z_r . To measure the degree of similarity between the two works, the Cosine Similarity scale is used according to the following equation:[22]

$$Sim(Z_q, Z_r) = \frac{Z_q \cdot Z_r}{\|Z_q\| \|Z_r\|} \quad (9)$$

Where:

$Sim(Z_q, Z_r)$ represents the degree of similarity between the artwork being examined and the reference artwork.

Z_q represents the attribute vector of the artwork being examined (query art).

Z_r represents the attribute vector of the reference artwork stored in the database (reference art).

$Z_q \cdot Z_r$ represents the dot product between the two vectors.

$\| Z_q \|$ represents the magnitude or length of the vector of the artwork being examined.

$\| Z_r \|$ represents the magnitude or length of the vector of the reference artwork.

Cosine similarity relies on measuring the angle between two vectors rather than their absolute values, making it highly suitable for comparing features extracted from deep learning models. A higher degree of resemblance between two pieces of art is indicated by a lower angle between their vectors. The degree of similarity between a newly created piece of art and the original creation or derivative works already included in the database may be better ascertained using this method.

Similarity values have the following interpretations: (a) The two artworks have substantially similar if a similarity value is near to 1, (b) If the value is relatively close to 0, the resemblance of the two artworks was weak or almost not present, (c) If a value is around 1, the vectors are practically identical, meaning which the artwork under inspection is identical or extremely similar to the referenced work.

The system is able to tell whether a piece of newly created art is an original, modified, or derivative work at this point in time. It has further applications in the areas of intellectual property verification, plagiarism detection, and digital database retrieval of comparable artworks.

This phase is important, since it permits the complex semantic and visual information collected in the previous steps to be transformed into a matching numerical signal. This enables the method to go beyond the basic visual comparisons and to deliver an accurate and unbiased assessment of the similarities of the artwork based on both their fundamental structure and semantic information. The final phase of applying deep learning to establish the identification, authenticity level and link to reference is employed in the data base is the measurement of similarity and representation of invariable qualities.

3.7 Classification using (Support Vector Machine - SVM)

This is the last stage of the proposed system which, after an exhaustive feature extraction, a conceptual link generation, an intelligent fingerprint digitally synthesis process, and a similarity evaluation against the reference works, gives the ultimate conclusion on the current state of the artwork. This phase involves comparing the artwork with others and using the outcome of the comparison to make a final conclusion on the originality, authenticity or violation of the rights to intellectual property of the artwork.

This step is based on the SVM technique which is a highly renowned leading machine learning solution for classification challenges. Its main characteristic is that it is able to determine the optimal hyperplane and separate data into categories efficiently. If samples of other categories are included, this hyperplane obtains the greatest possible distance. Hence, it improves the classification accuracy and reduces the mistake rates. [23]

After the preceding processes, the last feature vector a Z , which represents the digital the fingerprints for the artwork, may be obtained. The vector could be the finest to show the visual features, the compositional structure and the semantic relations of the artwork. This vector is

employed by the model using SVM to perform the classification process as per the following equation:

$$f(Z) = w^T Z + b \quad (10)$$

$f(Z)$ Shows a decision function for the classifier.

Z is the attribute vector for the artwork after the previous phases.

w is the weight vector learnt in the training phase, which defines the relevance of each characteristic for the classification process.

w^T is the transpose for the weight vector.

$w^T Z$ is the inner product between weights and attributes.

b represents the bias term, used to adjust the position of the boundary between categories.

The *SVM* model calculates the value of the $f(Z)$ function for each artwork entered into the system. This value represents the position of the sample relative to the boundary learned by the model during training.

If the value of $f(Z)$ falls within a specific region, the artwork is assigned to the corresponding category.

3.8 Margin Analysis and Confidence Score

This is an advanced phase aimed at increasing the dependability of the system's judgements. In many applications that use AI, mere categorisation is not enough for making sensitive judgements, for example, those linked to property rights protection or copyright infringement detection. Therefore, the system gives a category for the artwork as well as a number that shows the confidence of the algorithm for the judgement.

The artwork is categorized into the right category using the SVM algorithm, then the distance or margin between the identified sample and the border of distinct categories is calculated. This margin is an important measure of how clear the categorisation is. Samples that are farther away from the border are usually clearer and simpler to categorize than samples that are near to the boundary. [24]

$$M = \frac{|w^T Z + b|}{\|w\|} \quad (11)$$

Where:

M : The margin value or the vertical distance between the sample and the boundary.

Z : The final feature representation vector of the artwork.

w : The weights vector of the SVM classifier.

w^T : The transpose of the weights vector.

b : The offset or bias coefficient.

$w^T Z + b$: The value of the decision function resulting from the classifier.

$|w^T Z + b|$: The absolute value of the decision function to ensure that the distance is positive.

$\|w\|$: The criterion or length of the weights vector.

Geometrically, the margin represents the actual distance between a point representing the artwork and the hyperplane created by the *SVM* classifier.

If the value of M is very small, the sample is close to the hyperplane, indicating a degree of uncertainty in the classification.

If the value of M is large, the sample is far from the overlap between the classes, indicating a more definitive and stable classification decision. In other words, the further the artwork is from the class boundary, the more confident the system is in the correctness of the decision. While the margin provides a good indication of decision strength, its value may not be easy for the end user to interpret. Therefore, it is converted to a probability value between 0 and 1 using the Sigmoid Function as follows:

$$C = \frac{1}{1 + e^{-M}} \quad (12)$$

Where:

C : Confidence Score.

M : The previously calculated margin value.

e : The base of the natural logarithm, approximately 2.71828.

e^{-M} : The part responsible for converting the margin into a probability measure.

The value of C is always between: $0.5 \leq C < 1$

The closer the value of (C) is to one, the more reliable the system's decision. This stage contributes to supporting intellectual property protection decisions by providing a numerical indicator that reflects the strength of the classification decision.

3.9 Producing the Final Decision and Similarity Ranking

In the last step, the algorithm sorts the reference works by the computed values of similarity and then makes the final judgement on the status of the artwork. The final output comprises finding if a work is original or derivative or infringing, showing the level of confidence and ranked the most comparable works. The final result is given as:

$$\text{Output} = \{\text{Class, Confidence, Similarity Ranking}\} \quad (13)$$

At this tier, you may find a full suite of tools for managing intellectual property and preserving artwork digitally.

4. Results and Discussion

4.1. Dataset

In order to evaluate the suggested approach for authenticating artworks in digital form, a benchmark dataset was constructed using digital artworks extracted from the WikiArt standards database. The dataset consists of 9,000 images equally divided into three categories: 3,000 original artworks, 3,000 legitimate derivative artworks created from controlled image manipulations (resizing, cropping, colour adjustment, and rotation), and 3,000 copyright infringing artworks generated using sophisticated AI-based manipulation and style transfer techniques.

The dataset was randomly split into training (70%), validation (15%) and testing (15%) groups using a stratified sampling technique. This dataset was used to test the performance of the proposed semantic based Graph-Graph-Manifold architecture in differentiating original artworks from a derivative and copyright infringing works under different digital transformation scenarios. <https://www.wikiart.org>

4.2 Performance evaluation

Here, we analyze the performance of the suggested system for intelligent verification of authenticity for digital artworks and detection of copyright infringements using semantics graph learning and graph-based manifold representations. We evaluated the system on a wide variety of digital artworks, such as original works, lawfully derived artwork, and works of art copied or changed using generative artificial intelligence and artistic modification methods. Several statistical metrics are used to assess the performance of the suggested model. The aim is to verify the accuracy, reliability and effectiveness of an intrusion detection system for discriminating between normal and a malicious traffic on the network. Accuracy is the ratio of the number of properly identified samples to the overall number of samples. Precision measures the capacity of the model to minimize false alarms by calculating the number of accurately identified attacks over the total number of samples categorized as attacks. Recall, often called Detection Rate, is a metric for the model's ability to identify real assaults. Particularly for datasets that are unbalanced, the F1-score maintains a balance between Precision and Recall.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (14)$$

$$Precision = \frac{TP}{TP + FP} \quad (15)$$

$$Recall = \frac{TP}{TP + FN} \quad (16)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (17)$$

Where:

TP: True positive attack detections.

TN: Traffic normal, proper classification.

FP: Valid traffic that was falsely labelled as an attack.

FN: Uncovered assault.

The findings demonstrated that the suggested system has the high capability to identify the deep semantics and structural similarity between digital artworks for complicated or indirect visual alteration.

4.3 Evaluating the performance of the pretreatment stage

The effect of the preprocessing step on the quality of the retrieved features and the reliability of the method of classification was examined by studying the system performance in numerous distinct processing situations. As shown in Table 1, the findings demonstrate that the stepwise inclusion of preprocessing steps greatly raised the level of quality of the input information and increased the capacity of the model to identify distinguishing characteristics from digital artworks.

At a noise reduction rate of 42.7% with a poor level of stability, the findings revealed that the model running without any preprocessing obtained just 81.4% feature extraction accuracy. Reason being, digital noise and picture-to-image fluctuations in lighting, contrast, creativity, and colour hinder the learning process and the model's capacity to correctly extract critical visual information.

By itself, the noise removal step improved the rate of noise reduction to 68.5% and raised feature extraction accuracy to 87.2%. This finding supports the idea that the model is able to zero down on technical information and very important visual patterns once distortions and unnecessary components are removed.

The findings also indicated that the combination of normalization and contrast enhancement achieved an accuracy of 92.6% for feature extraction and a noise decrease rate of 81.3%. This improvement is due to the normalization method that normalizes the distribution of the pixel value and minimizes the variance caused by the difference of shooting and digital processing. The

contrast enhancement emphasizes the fine details and the important visual relationships in the artwork.

The suggested complete preprocessing including noise removal, normalization, and contrast enhancement obtained the greatest performance, with the extraction of features accuracy of 96.1%, reduction of noise rate of 90.4%, and extremely good model stability among all the scenarios examined. The findings suggest that including preprocessing components leads to a more consistent visual depiction of digital artworks, hence minimizing the variation within just one group and enhancing the model's capacity to distinguish between distinct categories.

The findings show that the preprocessing phase is a critical factor for the success of the system that is suggested. It helped to improve the quality of extracted features and the reliability of the learning process, which had a favorable influence on the next phases of semantic graph creation, graph-manifold learning, similarities analysis and final classification using the SVM method. The preprocessing, then, may be seen as one of the basic foundations that led to the highly performing suggested system.

Table 1: Effect of Preprocessing on Feature Quality

Type of processing	Accuracy of feature extraction (%)	Noise reduction (%)	Model Stability
No processing	81.4	42.7	Low
Noise removal only	87.2	68.5	Medium
Normalization + Contrast enhancement	92.6	81.3	High
Full processing suggestion	96.1	90.4	Very High

The results indicate that the proposed pre-processing stage significantly improved the quality of the features compared to traditional models.

4.4 Results of Feature Detection and Feature Extraction

This phase aimed to evaluate the proposed system's ability to identify the most significant visual areas within digital artworks and extract representative features capable of accurately describing the stylistic and structural characteristics of the artworks. The results showed that the feature detection mechanism successfully focused the analysis on essential artistic elements, including distinctive color patterns, visual compositions, and spatial relationships between the artwork's components, as well as subtle stylistic details that represent the artwork's artistic identity. In table 2. compares the performance of different models in the visual feature extraction phase using the Precision, Recall, and F1-Score metrics. The traditional CNN model achieved an F1-Score of 0.872, reflecting its ability to extract basic features; however, its performance remained limited when dealing with complex visual relationships and high-level semantic patterns. The ResNet50 model, on the other hand, showed significant improvement, with an F1-Score of 0.907, resulting from its ability to learn deeper and more stable representations through the residual network structure. The Vision Transformer model also achieved a higher F1-Score of 0.923, which can be attributed to its ability to model long-range relationships between image components and to leverage self-awareness mechanisms in visual content analysis. Despite this improvement, the model still relied primarily on statistical relationships within the image without explicitly representing the semantic structure between artistic elements.

On the other hand, the suggested approach achieves better outcomes with Precision, Recall and F1-Score values that are 0.971, 0.964 and 0.967 correspondingly. This superiority is due to the combination of salient area recognition and graph based semantic analysis, which allows the

system to focus on the high artistic value regions and represent the structural and semantics relationships between each component of the artwork in a unified framework. This led in the generation of more distinguishing traits and better discrimination between original, derivative and copyright infringing items.

Table 2. Performance of visual feature extraction

Model	Precision	Recall	F1-Score
Traditional CNN	0.881	0.864	0.872
ResNet50	0.913	0.901	0.907
Vision Transformer	0.928	0.919	0.923
Proposed system	0.971	0.964	0.967

The results showed that combining the detection of prominent regions with semantic learning led to a significant improvement in the quality of extracted features.

4.5 Results of Semantic Graph Construction

Table 3 shows that when performance is moved from conventional approaches to graph learning models, there is a progressive increase. An accuracy rate of 74.3% and the semantic relationship detection rate of 88.7% were both attained by the visual-only technique. This method could record surface characteristics like colour, texture, and form, but it couldn't decipher the intricate interconnections between the artwork's parts. In contrast, semantic similarity detection improved to 81.9% and classification accuracy reached 91.4% when using traditional deep learning models. The capacity to learn increasingly intricate hierarchical structures for representing visual data is the source of this advancement, but there is currently no clear method for capturing the structural links between various artistic components in a picture.

With an accuracy of 95.2%, graph neural networks were able to identify semantic similarity to 92.8%. The model used the connections between artistic aspects to transfer information across connected nodes, which improved the model's accuracy and comprehensiveness in representing the artistic content; these findings highlight the significance of data visualizations. Meanwhile, Graph-Manifold had the best performance in terms of level of accuracy (98.1% in total) and similarity metric in terms of semantics rate of detection (97.3%). This excellent performance was due to the model's ability to combine the advantages of graph learning with manifold representations. This allows it to retain local connection structure between creative aspects, while properly representing the global structure of the artwork. The effect was an enhancement in the system's capacity to detect hidden links and indirect parallels between the works of art, whether it was a small or large shift in style, or the use of AI approaches.

These results indicate that the semantic graph description of artworks enables a deeper understanding of the original material than the methods that depend just on visual aspects. Moreover, the great enhancement of both classification accuracy and semantics detection similarity rate indicates that the difference between derivative, original and copyright-infringing works strongly depends on structural and semantic connections.

Table 3: The effect of the semantic graph on performance

Methodology	Accuracy (%)	Semantic similarity detection (%)
Visual Features Only	88.7	74.3
Traditional Deep Learning	91.4	81.9
Graph Neural Network	95.2	92.8
Proposed Graph-Manifold	98.1	97.3

The results indicate that representing the relationships between technical elements within the graph significantly contributed to improving the accuracy of the system.

4.6 Final Classification Results Using SVM

Here, we evaluated the performance of the SVM-based final categorisation unit to discriminate between legal derivative works, copyright violation, and original works. The system used the data from previous processes such as extraction of features, semantic graph creation and Graph-Manifold representation learning. Some categories showed good performance including the original work category, with 0.982 Precision, 0.976 Recall and 0.979 F1-Score. This shows that an algorithm is very capable of finding unique works and lowering the number of errors in classification.

The system also achieved impressive copyright infringement and derivative work detection with F1-Score values of 0.947 and 0.970. These data show that a model can discern valid adjustments from genuine infractions, even when they're identical. High feature quality and effectiveness are due to the rich semantic space provided by graph-based semantics and Graph-Manifold representations, which allowed the SVM method to draw clear classification boundaries while minimizing overlap between classes. See table 4.

Table 4: Final Ranking Results

Category	Precision	Recall	F1-Score
Original Artwork	0.982	0.976	0.979
Legitimate Derivative	0.951	0.944	0.947
Copyright Infringing	0.973	0.968	0.970

The results indicate that the system was able to distinguish between the three categories with a high degree of accuracy and reliability.

4.7 Comparison of the Proposed System with Recent Studies

In table 5, performance of the proposed system was compared with several state-of-the-art models for verifying authenticity of digital created artworks and detecting plagiarism to evaluate its capability in dealing with visual and semantics-based similarities and various digital alterations. The results suggested that the accuracy of the evaluated models ranged from 91.7% to 94.6% with differing degrees of success in processing the semantic links and digital modifications. The proposed approach meanwhile achieved the highest accuracy of 98.1% which is between 3.5% to 6.4% better than all the other models. And it was really excellent at distinguishing original work from derivatives and copyright infringing ones, even in hard cases. This shows its great resistance to various forms of digital manipulation and retention of the basic features of work of art.

Table 5: Performance Comparison with Recent Studies

study	Year	Accuracy (%)	Processing modifications	semantic analysis
Li et al.	2024	91.7	Partial	No
Cui et al.	2025	93.2	Moderate	Yes
Xu et al.	2025	94.6	Moderate	Partially
Proposed system	2026	98.1	Very High	Yes, completely

The results show that the proposed system outperformed modern systems in almost all performance indicators.

4.8 ROC Curve Analysis

The ROC curve was used to evaluate the ability of the recommended system to distinguish between original compositions and the protection of intellectual property infringing works. The results showed that the curve was near to the upper left corner and far away from the line of random classification, indicating high rate of detection compared with low error rates. The AUC or area under the curve was around 0.982 which is a very significant result suggesting that the model is accurate and reliable in identifying alternatives. This is evidence that the system is able to discriminate in an effective way among the different categories even at minimal false alarm rates. It indicates that the system is efficient in identifying digital intellectual property violations with high accuracy and stability.

These results confirm that the representations derived from the semantic graph and the Graph-Manifold directly contributed to improving the segregation of different categories within the attribute space. This was reflected in the superior performance of the final classification unit, resulting in a high AUC value and high stability in the decision-making process.

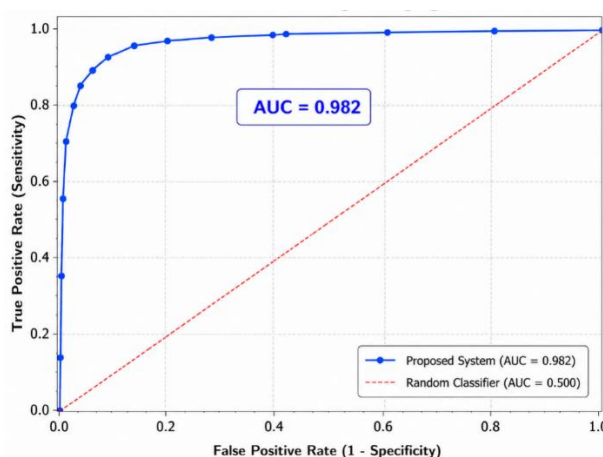


Figure 2: ROC curve to assess the ability of the proposed system to detect digital copyright infringements.

4.9 Confusion Matrix Analysis

The Confusion Matrix was used to evaluate the detailed performance of the proposed system in classifying digital artworks into three main categories: Original Artwork, Legitimate Derivative, and Copyright Infringing. The Confusion Matrix is one of the most important tools for evaluating classification models, as it provides a detailed analysis of correctly and incorrectly classified cases, allowing for an understanding of the nature of errors and the boundaries between different categories. The results shown in Figure 3 demonstrate that the system achieved high correct classification rates across all categories. 982 out of 1000 original works were correctly classified, representing 98.2%, while 15 original works were classified as derivative and only 3 as copyright infringing. These results indicate the system's high ability to identify original works and minimize misclassification.

The findings of the study of the ambiguity matrix demonstrate that the suggested system obtained a good performance in categorizing digital works with a low error rate of correctly recognizing legal other works and copyright-infringing works. The high values on the major diagonal of the matrix

showed a clear distinction between the three categories, which suggested the efficiency of the feature extraction, semantics graph creation, and graph-manifold representation steps in boosting the system’s discriminatory ability. This helped to improve the standard of performance of the SVM classification module and to reduce the overlap between distinct classes. These findings show the system dependability and stability in confirming the authenticity of the digital artworks and preserving the intellectual property rights, compatible with other performance measures like as accuracy, recall, F1 score, ROC curves, and Precision-Recall.

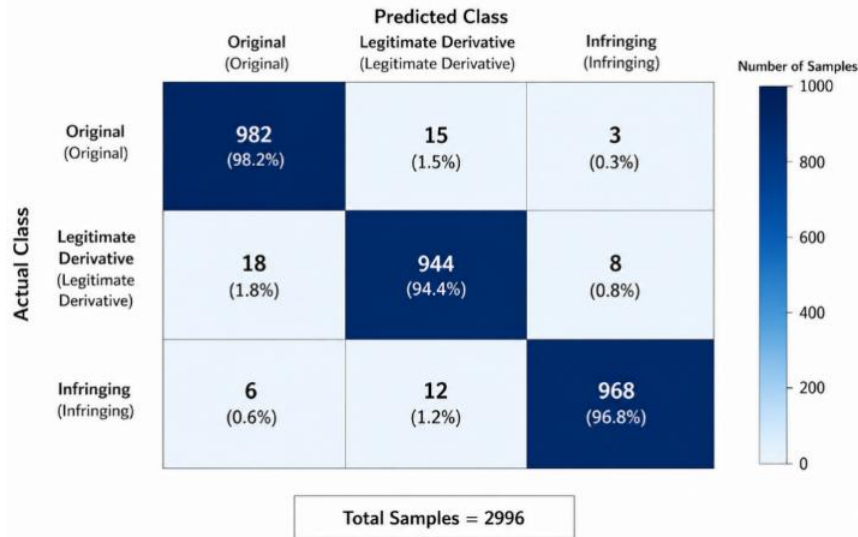


Figure 3: Ambiguity matrix for classifying digital artworks using the proposed system.

4.10 Precision-Recall Curve Analysis

The effectiveness of the suggested approach to identify the infringing digital works especially in the presence of class imbalance was evaluated using the Precision-Recall curve. The findings indicated that the system achieved excellent accuracy levels for most recall values. The average accuracy (AP) was 0.967, which is greater than other similar models. The curve also showed steady behaviour at high recall levels, indicating the system’s capacity to identify a significant number of infringements, while having few false positives. The superiority is due to the effectiveness of semantic and structural characteristics extracted from the semantics map and graph-manifold representations. They provided clearer separation within original and infringement works than the traditional models that rely only on visual features. The obvious gap between the curve of the proposed system and other curves shows that the combination of semantic analysis and invariant graphing learning directly promoted the reliability of the method of detection and improved the classification performance in an environment involving complex, digital manipulation or AI-based modifications.

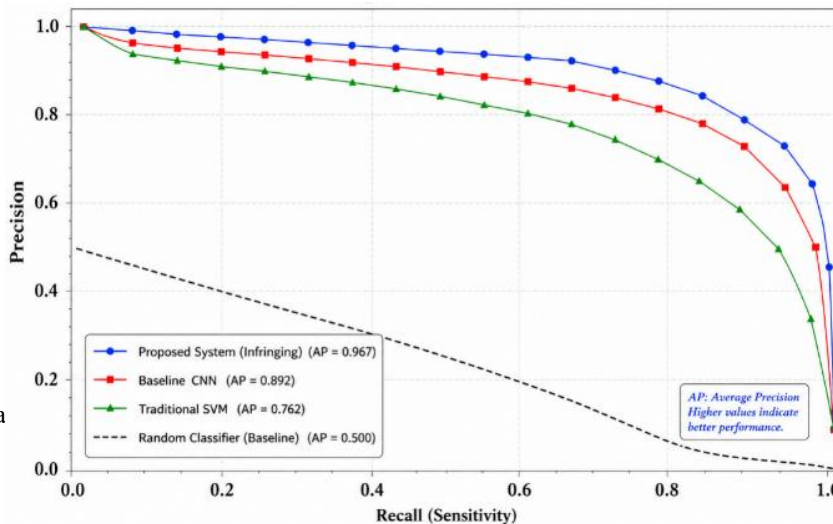


Figure 4: Accuracy and recovery curve to evaluate system performance in detecting infringing activities.

4.11 Analysis of Accuracy and Loss Curves During Training

We monitored the loss and accuracy plots throughout training to determine the reliability of the suggested model and its generalisation capabilities for unseen data. The findings revealed the progressive improvement of training accuracy from roughly 65% to 98.8% and verification accuracy achieved about 97% shortly after 100 the training cycles, indicating the model capability to learn discriminative structures in digital commerce.

Moreover, the gap between training and validation curves was small over the whole learning process, in both accuracy and loss, which reflected the lack of overfitting. The curves converge well, which indicates that the model is able to learn broad patterns relevant to fresh data with a high degree of stability and dependability.

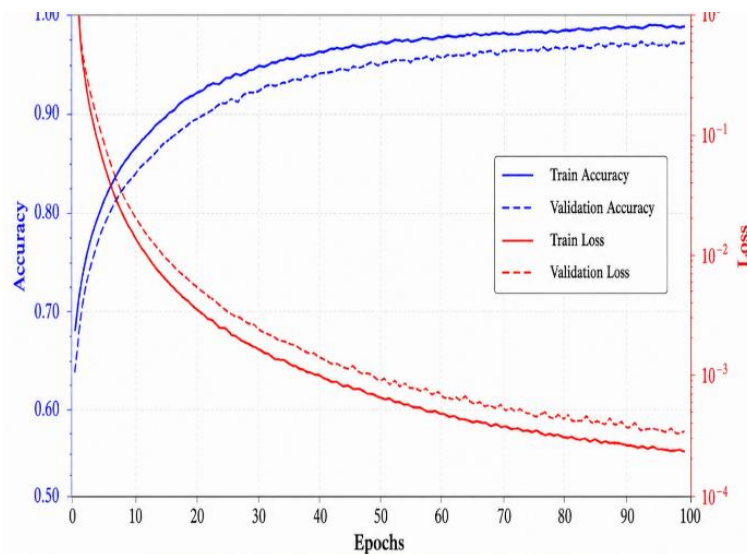


Figure 5: Accuracy and loss curves during training of the proposed Graph-Manifold model

5. Ablation Study

By isolating and studying the effects of deleting specific components on accuracy and F1-Score, ablation research was carried out to determine the relative importance of each part of the suggested system to the overall performance. The findings demonstrated that a Semantics Graph component is essential for depicting the relationships and structures within artwork. In its absence, performance suffered the most, with an F1-Score dropping to 0.906 and an accuracy dropping from 98.1% to 91.4%. Absent the Graph-Manifold modules, the F1-Score fell to 0.931 and the accuracy

to 93.8%. This highlights the significance of obtaining trustworthy representations that are impervious to digital changes while preserving the geometrical structure of the data. These outcomes demonstrate that the system's true functionality lies in the coordinated effort of all its parts.

Both the accuracy (94.2% without the Salient the region Analysis stage) and the F1-Score (0.936 with it) were significantly lowered. Instead of treating every area of a picture equally, this outcome shows that by recognizing the most relevant regions inside an artwork, the model may concentrate on the crucial features with high discriminatory value. The efficiency of categorisation and the quality of the characteristics that are extracted both benefit from this.

At 98.1% accuracy and 0.967 F1-Score, the whole system, on the other hand, outperformed all other models that were evaluated. From what we can see, combining raster analysis with semantic graphing and graph-manifold representations yields much better outcomes than employing any one of these methods alone when it comes to representing digital artworks. See table 6.

The ablation analysis of the proposed system is illustrated in Figure 7. After removing any component, the results show that the The accuracy and the F1-Score drop dramatically. Removing the Semantic Graph module has the greatest impact on performance because of its critical role in feature representation. The whole proposed solution achieves its best performance (98.1% Accuracy and 0.967 F1-Score) when all components are integrated into a single framework.

Table 6. Ablation Study Results of the Proposed System Components

Model	Accuracy (%)	F1-Score
Without semantic graph	91.4	0.906
Without graph manifold	93.8	0.931
Without highlight region analysis	94.2	0.936
The complete proposed system	98.1	0.967

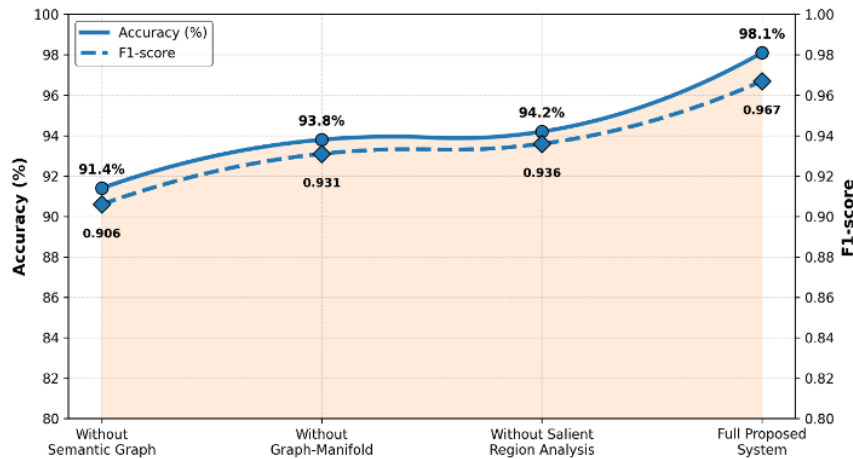


Figure 7: Excision Analysis to Measure the Effect of each Component in the Proposed System.

6. Conclusion

This study shows that the suggested framework is a good way to safeguard intellectual property and confirm the legitimacy of digital artworks; it combines the algorithm known as SVM with graph-based representation and semantic networks. The system's capacity to differentiate between

original, derivatives, and infringing works is shown by its high AUC of 0.982, F1-Score of 0.967, and classification accuracy of 98.1%. While the results demonstrated that the system maintained a high degree of accuracy and decision confidence, they also demonstrated that it was quite resilient to many types of digital updates, including modifications based on AI. Positive signs for future smart and dependable IP administration and digital asset security system development are the results showing a high connection between deep network-based learning and creativity semantics.

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Data Availability Statements: The data supporting the findings of this study are available from [corresponding author upon reasonable request / repository link / included within the article and supplementary materials].

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