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A LogoXPose: Unmasking Fake Logos with AI

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Abstract—**Brand logos are essential for product identification and for maintaining the reputation of businesses. However, the increasing presence of counterfeit products and manipulated digital content has led to the widespread misuse of fake logos. Manually detecting such counterfeit logos is difficult and time-consuming, especially when dealing with large volumes of images and videos on digital platforms. With the advancement of deep learning (DL) techniques such as Convolutional Neural Networks (CNNs), computer systems have achieved significant success in image classification and feature extraction tasks. This paper presents an automated logo authentication system that uses deep learning to detect and classify logos from images and videos as real or fake. The proposed system integrates YOLOv7 for logo detection with a CNN-based classifier for authenticity verification. The system is capable of detecting multiple logos within a single image or video frame and classifying them accurately. Furthermore, the framework provides audio-based verification for recognized brands and generates a detection report for further analysis. By offering a fast and automated method for identifying counterfeit logos in digital media, the proposed approach contributes to improving brand protection.**

Index Terms—**Deep Learning, Convolutional Fake Logo Detection, Convolutional Neural Network (CNN), YOLOv7, Deep Learning, Computer Vision, Brand Authentication.**

I. INTRODUCTION

Brand logos are essential for product identification and upholding businesses' reputations. However, the abuse of fake logos has greatly increased due to the quick expansion of digital advertising, social media, and online marketplaces. Fake logos can mislead consumers and undermine the legitimacy of legitimate brands because they are frequently used in counterfeit goods, deceptive advertisements, and altered digital content [1], [2]. Early detection of such fake logos is crucial for protecting brand identity and averting financial losses. Nevertheless, the current techniques for spotting phony logos mostly depend on manual examination of photos or product packaging, which can be laborious, necessitate specialized knowledge, and be prone to mistakes and inconsistencies [3],[4]. Therefore, there is a need to develop an intelligent system that can automatically detect and verify logo authenticity from digital images and videos. Recent developments in deep learning, especially Convolutional Neural Networks (CNNs), have made automated systems remarkably successful in tasks like object detection and image classification. CNN models can automatically extract intricate visual features from images and recognize patterns that are challenging to find with conventional techniques [8], [9]. In a similar vein, object detection algorithms like YOLO (You Only Look Once) have shown remarkable speed and accuracy in identifying objects in images and video streams [11], [12]. These deep learning methods offer a practical way to identify and categorize logos in digital media.

In this study, we present LogoXpose: Unmasking Fake Logos with AI, a deep learning-based system that uses image and video inputs to identify and categorize logos as authentic or fraudulent. The main goal of this work is to create an automated framework that combines a Convolutional Neural Network (CNN) model for authenticity classification with YOLOv7 for logo detection. The technology can correctly identify and categorize various logos in pictures and video frames. The suggested solution also produces a detection report for additional study and offers audio-based verification for well-known brands. It is anticipated that this approach will increase the effectiveness of detecting fake logos and help safeguard brand identification in digital settings.

II. PROBLEM STATEMENT

The fast proliferation of counterfeit goods and distorted digital media has made it more crucial than ever to detect phony logos. Conventional techniques for spotting phony logos mostly rely on the laborious and frequently human error-prone manual examination of pictures and videos. Numerous computer-based solutions already in use have trouble correctly identifying multiple logos in complicated images or successfully differentiating between real and fake logos. Thus, an intelligent and trustworthy automated system that can effectively identify brands from photos and videos and accurately categorize them as authentic or fraudulent is required. In order to enhance brand protection and trust, the system should also be able to recognize several trademarks in a single frame and offer extra verification functions.

III. LITERATURE REVIEW:

A. Overview of Existing Research:

Viveghaa and Heamalatha (2024) [1] proposed a method for detecting fraudulent logos that uses image processing techniques to find bogus brand logos. In order to identify if a logo is authentic or fraudulent, their approach concentrated on examining visual elements including color patterns, forms, and textures. To find discrepancies, the model processed input photos and compared them with reference logo databases. The algorithm was able to identify modified or fraudulent logos in numerous instances, according to experimental data. Nevertheless, the approach's primary reliance on conventional image processing methods restricted its capacity to manage intricate images and big datasets. Therefore, more advanced deep learning techniques are required to improve the system's detection capability.

Bhattacharya et al. (2023) [2] developed a machine learning-based online bogus logo identification system that categorizes logos according to their visual attributes. The suggested approach was made to function on online platforms where users contribute photos to confirm the legitimacy of logos. To ascertain whether a logo is authentic or fake, the model employs classification algorithms to extract significant information from photos. When compared to manual inspection techniques, the system showed increased detection accuracy. Large datasets were necessary for improved training and generalization, and the performance was reliant on the quality of the input photos. This highlights the importance of building more robust models that can perform effectively in real-world environments.

Raut et al. (2023) [3] introduced a Fake logo detection method that analyzes and recognizes forged brand logos using image processing techniques. Preprocessing the photos, extracting elements like edges and forms, and comparing them with stored authentic logo patterns comprised their methodology. In controlled datasets, the system performed well in detecting fake logos. The findings demonstrated that image processing techniques can help identify visual alterations in logos. Nevertheless, the system was unable to handle several brands in a single image and had trouble identifying logos in complicated backdrops. Hence, advanced detection algorithms are required to improve accuracy in real-world applications.

Thilagaraj et al. (2024) [4] provided a thorough analysis of machine learning and deep learning methods for detecting phony logos. In order to identify fake logos, their study examined a variety of methods, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and other deep learning frameworks. According to the review, deep learning algorithms that automatically extract complex visual information from photos greatly increase detection accuracy. The scientists did, however, also highlight difficulties like little datasets, high processing demands, and the need for more reliable systems with real-time detection capabilities. Their findings indicate that further research is necessary to develop efficient and scalable fake logo detection systems.

Yadav and Swarnalatha (2024) [5] proposed a machine learning-based approach for detecting false logos was suggested by Yadav and Swarnalatha (2024) [5]. It focuses on using extracted picture attributes to identify logos as authentic or counterfeit. The system analyzed patterns and inconsistencies in logos using feature extraction techniques and machine learning classifiers. According to experimental findings, the model identified phony logos from a variety of brands with a promising degree of accuracy. Even though the system worked well, it needed to be improved in order to handle real-world situations when logos appear in various sizes, orientations, and lighting conditions. Therefore, to improve detection performance, more sophisticated deep learning approaches are required.

Preeti and Santhi Sri (2023) [6] introduced a Region-based Convolutional Neural Networks (R-CNN) are a deep learning-based method for detecting fake logos. By examining intricate visual characteristics, the suggested approach finds logos in photos and confirms their legitimacy. The model showed a high degree of detecting skill when it came to spotting phony logos in pictures of e-commerce products. When compared to conventional techniques, the application of R-CNN enhanced localization and classification results. However, the model's usefulness in real-time systems was limited due to its high computational resource requirements and lengthy processing time. Optimizing the model for quicker and more effective identification should be the main goal of future developments.

Rayapati et al. (2023) [7] proposed a YOLO (You Only Look Once) object detection technique used in a false logo detecting system. The model was trained to recognize logos in pictures and determine if they are authentic or fake. YOLO made it possible to quickly identify and locate logos in complicated pictures and video frames. When compared to previous object detecting methods, experimental results demonstrated increased speed and accuracy. To handle tiny logos and overlapping items in busy settings, the system still needed to be improved. This indicates that detection accuracy and resilience still need to be improved. In addition, integrating advanced deep learning classifiers can further improve the reliability of fake logo detection systems.

Gupta et al. (2023) [8] presented a machine learning-based approach for detecting logo infringement that is intended to find instances of unapproved use of brand logos. Their methodology used image comparison methods and machine learning classifiers to examine logo similarities. Potential copyright infringements and fake logos in digital material could be identified by the system. In recognizing logo misuse across various datasets, the experimental findings showed good performance. To increase detection accuracy and scalability for extensive real-world applications, the study did point out the need for more sophisticated deep learning models. Fake logo identification systems can therefore be greatly improved by combining deep learning and object detection approaches. Furthermore, future systems should focus on improving real-time detection capabilities for large volumes of digital media

B. Techniques Used

The Previous research on fake logo detection has used various image processing, machine learning, and deep learning techniques to identify fraudulent logos in digital images. Convolutional Neural Networks (CNNs) are widely used for automatic feature extraction and classification because they can learn complex visual patterns such as shapes, colors, textures, and edges present in brand logos. Deep learning architectures such as ResNet, MobileNet, Inception, and other CNN-based models are frequently used because they improve classification accuracy and detect subtle differences between genuine and fake logos. These models help automate the detection process and reduce the limitations of manual inspection. Several researchers have also applied object detection algorithms such as YOLO (You Only Look Once) and Region-based Convolutional Neural Networks (R-CNN) to locate logos within images before verifying their authenticity. These detection algorithms can recognize multiple logos in a single image or video frame and provide faster processing than traditional methods. In many systems, the detected logo region is passed to a classification model to determine whether the logo is genuine or counterfeit, which improves the accuracy and reliability of fake logo detection systems. In addition, data augmentation techniques such as image rotation, flipping, scaling, and brightness adjustments are commonly used to increase dataset size and improve model generalization. Some studies also use feature extraction and machine learning classifiers to analyze logo patterns and identify similarities with genuine brand logos. These approaches help improve the robustness of detection systems when logos appear in different sizes, orientations, and backgrounds. Overall, the integration of deep learning models with advanced detection algorithms has significantly improved the performance of automated fake logo detection systems.

C. Gaps identified:

Despite the great accuracy reported by numerous studies on false logo detection, there are still a number of unanswered research questions. Poor model generalization is a major problem because many systems are tested and trained on small or intentionally created datasets that might not accurately reflect digital media in the real world. Because of this, these models could not work well in other contexts, such social media photos, ads, or e-commerce sites. Since many research rely on tiny or single-source logo datasets, which can result in overfitting and biased conclusions, the availability of big and diverse datasets is another significant restriction. These detection techniques are less reliable since real-world differences such various image resolutions, lighting conditions, backdrops, and logo distortions are frequently overlooked. Furthermore, very few research concentrate on processing logos in video frames or identifying several logos inside a single image. Real-time deployment for practical applications is challenging due to the high computational resource requirements of many current models. Additionally, a number of deep learning models function as "black box" systems that fail to provide a clear explanation for the detection conclusion. An effective and trustworthy fake logo identification system is therefore required, one that can operate on a variety of datasets, identify several logos, and deliver precise and automated findings in practical situations. Conclusion summary

Overall, the numerous studies demonstrate that deep learning has a great deal of promise in the field of detecting false logos; numerous systems are able to distinguish between real and fake logos from digital photos with a high degree of accuracy. Logo recognition and categorization can be automated with the help of various CNN-based architectures, machine learning models, and object detection techniques like YOLO and R-CNN. This reduces manual labor and increases detection consistency. Systems are now able to identify logos in complicated photos and digital media platforms more effectively because to the integration of deep learning techniques with image processing methods. The review does point out that despite these developments, a number of issues still exist, such as imbalanced and small datasets, the difficulty of identifying logos in various lighting and background circumstances, and the high processing demands of certain deep learning models. Furthermore, many current algorithms are unable to interpret logos from video frames in real time or correctly identify several logos in a single image. It is crucial to create systems that are more effective, scalable, and able to handle a variety of real-world datasets while retaining high detection accuracy in order to overcome these constraints. These results offer a solid basis for the planned study, which attempts to create an automated framework for identifying and categorizing brands from photos and videos as authentic or fraudulent.

IV. IMPLEMENTATION

A. Overview:

Deep learning algorithms are used by the suggested method to automatically identify and categorize phony logos in pictures and videos. Data collection, data preprocessing, logo detection, logo categorization, and result generation are the five primary phases of the complete procedure.

B. System Design:

The suggested solution uses a modular pipeline-based design to make it possible to identify phony logos in pictures and video frames. Following the collection of logo images, preprocessing methods such data augmentation, normalization, and resizing are applied to enhance the quality of the photographs. To find and identify logos in the input image or video frame, an object detection technique like YOLO is used. Following the identification of the logo regions, a Convolutional Neural Network (CNN) model is employed to extract significant visual characteristics and categorize the logos as authentic or fraudulent. The system is able to identify and examine each logo separately within a single picture or frame. This pipeline ensures that the entire process from raw image input to logo detection, classification, and result

C. Data Collection and Preprocessing:

A dataset of brand logo photos gathered from publically accessible sources and research datasets was used to create and test the suggested deep learning model. The model can conduct binary classification because the dataset includes pictures of different brand logos that have been classified as authentic or fraudulent. To mimic actual phony logo situations, these photos feature a variety of modifications, including altered logos, changed colors, warped shapes, and counterfeit designs. All photos were preprocessed using noise reduction, normalization, and scaling to set input dimensions appropriate for the CNN model prior to model training. In order to expand the amount of the dataset and enhance model robustness and generalization performance, data augmentation techniques such random rotation, flipping, scaling, and brightness modifications were also used.

D. Model Architecture:
The approach under discussion uses a Convolutional Neural Network (CNN) architecture to identify and categorize company logos from photos and video frames as authentic or fraudulent. The CNN model was chosen because of its shown capacity to extract deep visual elements that are crucial for recognizing brand logos, such as forms, colors, edges, and textures. An object recognition method like YOLO was utilized to identify logo regions prior to classification in order to efficiently identify logos within photos. A CNN-based classifier is then given the identified logo regions to assess if the logo is authentic or fake. In this work, the model was updated for binary classification of logos using pretrained CNN weights. A Global Average Pooling layer, a Dense layer with ReLU activation, a Dropout layer to avoid overfitting, and a final Dense layer with Softmax activation for class prediction make up the network's final layers. With good detection accuracy and computational efficiency, this design allows the system to identify several logos in a single image or video frame. Additionally, the system can produce reports and detection findings that assist users in confirming the legitimacy of brand logos.

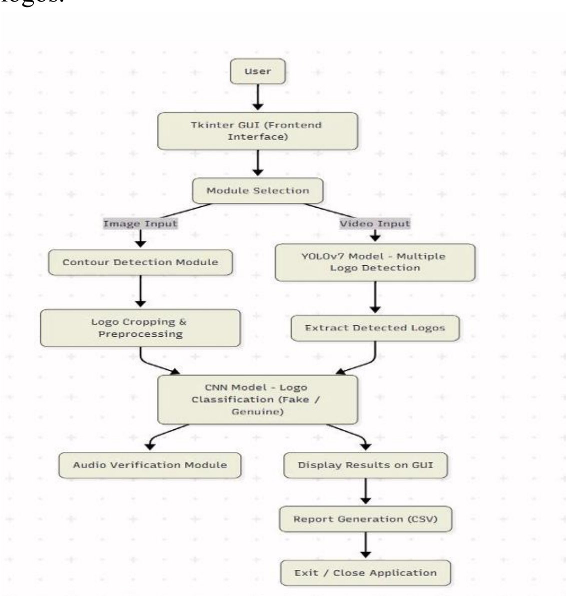

Fig. 1: Architectural diagram of proposed system

E. Training and Implementation:
The model was created in Python using deep learning frameworks like TensorFlow and Keras, and Google Colab's GPU support was turned on to speed up the training process. To properly assess the model's performance, the dataset was split into training and testing sets using an 80:20 ratio. To meet the input criteria of the CNN model used for classification, all logo images were scaled to 224 × 224 × 3 pixels. The Adam optimizer was employed with an initial learning rate of 1×10^{-1} and the binary cross-entropy loss function was utilized for training. To enhance model generalization and lessen overfitting, data augmentation methods like rotation, zooming, random flipping, and brightness modifications were applied during training. In order to preserve learnt features, the CNN model was trained in stages, with the feature extraction layers being trained first while the older levels were frozen. In order to enhance classification performance, later layers were adjusted with a lower learning rate of 1×10^{-1}. Early stopping, learning rate reduction, and model checkpointing.

V. RESULTS AND DISCUSSION

The proposed fake logo detection system was tested on a dataset consisting of multiple brand logos including both real and fake samples. The system was implemented using Python with deep learning libraries such as TensorFlow, Keras, PyTorch, and OpenCV. The CNN model was used to classify logos as real or fake, while the YOLOv7 model was used to detect multiple logos in images and videos. The trained CNN model successfully classified logos with high accuracy and demonstrated strong capability in identifying visual features such as shapes, textures, and color patterns that differentiate genuine logos from counterfeit ones. The system was evaluated using several test images and video samples to measure its ability to detect logos under different conditions such as varying lighting, backgrounds, and logo sizes. The results showed that the model was able to correctly identify genuine logos while accurately detecting manipulated or counterfeit logos present in the dataset. The integration of YOLOv7 detection with CNN classification also improved the system's capability to analyze complex images containing multiple logos simultaneously. Overall, the experimental results indicate that the proposed system provides an effective and automated solution for detecting fake logos in digital media.

Fig. 2 shows the confusion matrix used to evaluate the classification performance of the CNN model. The confusion matrix represents the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This matrix helps in understanding how accurately the model distinguishes between real and fake logos.

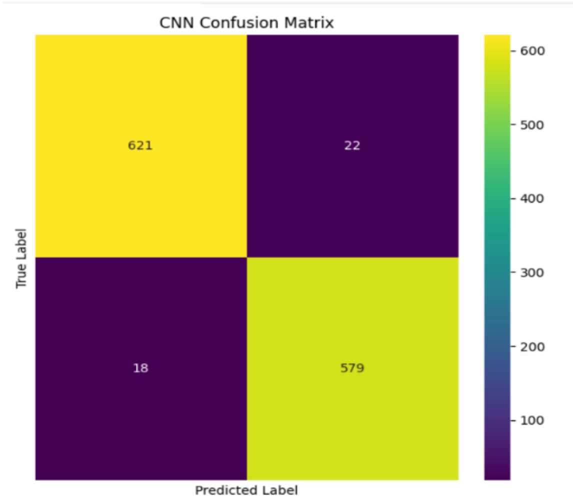

Fig. 2: CNN Confusion Matrix showing classification performance for logo images. The YOLOv7 model was utilized to identify several logos in a single picture or video frame in order to assess the system further. The model created bounding boxes around each detected logo after successfully identifying various logo regions. Following detection, the CNN classifier was used to identify if each logo region was authentic or fraudulent. The system's capacity to evaluate complicated situations with numerous logos at once was greatly enhanced by this combined detection and classification strategy.

Fig. 3: Real Logo Detection

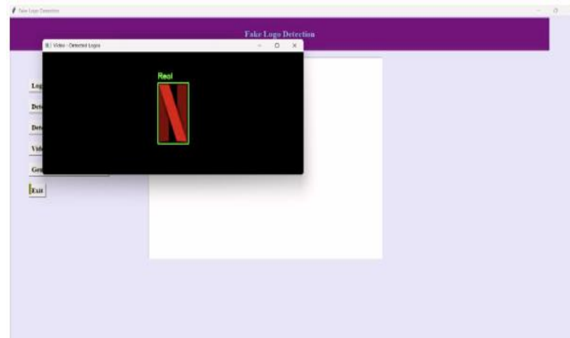

Fig. 4: Logo Detection in Video

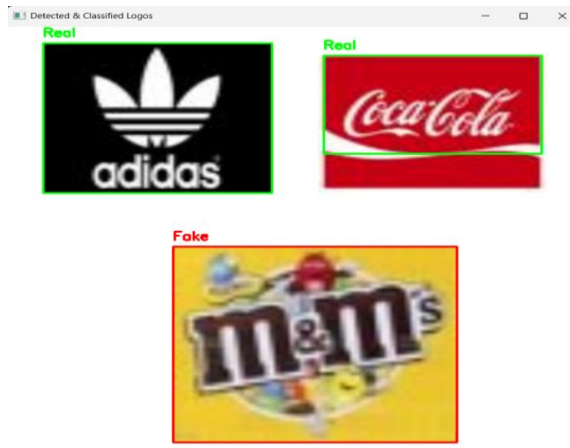

Fig. 5: shows sample detection results produced by the proposed system. The detected logos are highlighted using bounding boxes, where green boxes indicate genuine logos and red boxes represent fake logos in a single image.

Fig. 5 shows the successful integration of the contour based detection and CNN models by detecting and classifying multiple brand logos within a single image. The system effectively identifies distinct logo regions simultaneously, using green bounding boxes for genuine items like Adidas and red boxes for counterfeit samples like M&M's.

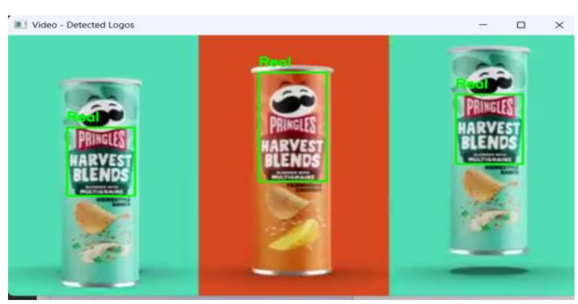

Fig. 6: Video frame detection results showing consistency across multiple products.

Fig. 6 shows the YOLOv7 model processed frames in real time to detect multiple logos appearing across different frames. The system effectively maintains detection consistency across multiple identical items in a single frame, such as the Pringles cans shown in the results, correctly labeling them as "Real" with a high degree of accuracy. This successful identification under varying lighting conditions, sizes, and orientations demonstrates the model's capability to handle the complex visual scales common in retail or warehouse environments.

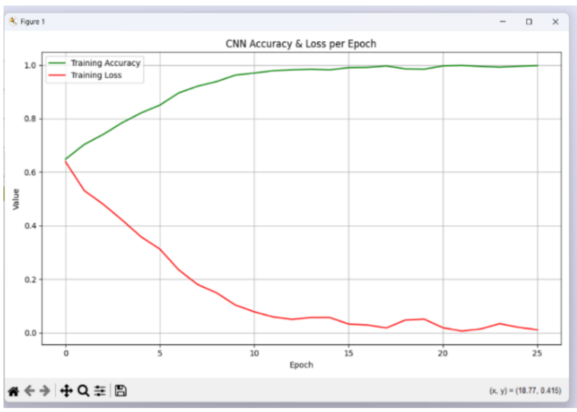

Fig. 7: CNN Training Accuracy & Loss per Epoch.

Fig. 7 shows the CNN model's training and validation accuracy and loss curves. While the loss steadily declines across epochs, the model shows a consistent improvement in accuracy over training. While the validation accuracy stayed near the training results, the training accuracy reached about 95%.

CNN-based Fake Logo Classification model is evaluated using Accuracy, Precision, Recall, and F1-Score. These metrics measure how effectively the system distinguishes between Genuine and Fake logos. The Precision indicates how many logos predicted as fake were actually fake, while Recall represents how many fake logos were correctly identified. The F1-Score provides a balanced measure of the model’s performance. Table 1 shows the evaluation results: method.

Metric	Percentage
Accuracy	96.46%
Precision	96.48%
Recall	96.48%
F1 score	96.45%

Fig. 8: Model Evaluation on Different Metrics

VI. CONCLUSION

The deep learning-based Fake Logo Detection system offers a quick and accurate way to spot fake logos in online content. While the YOLOv7 algorithm is used to identify various logos in pictures and videos, a Convolutional Neural Network (CNN) model is utilized to categorize logos as authentic or fraudulent. Users may upload photos or videos, check detection results, and get forecast confidence scores thanks to the integration with a straightforward graphical user interface, which lessens the need for human examination. Additionally, the technology enhances usability and brand authentication by supporting the creation of detection reports and audio-based verification for recognized brands. Overall, the proposed system improves the accuracy of fake logo detection, automates the verification process, and helps protect brand identity in digital platforms, and with further improvements it can become a powerful tool for combating counterfeit products.

VII. FUTURE WORK

The current Fake Logo Detection system performs effectively, but several improvements can make it more powerful and suitable for real-world applications. The model could be improved by training it on a larger and more diverse dataset of brand logos collected from different industries, digital platforms, and real market environments to improve generalization and reduce bias. In addition to the current CNN and YOLOv7 models, advanced techniques such as Vision Transformers or improved object detection models like YOLOv8 could be explored to enhance detection accuracy and speed. The integration of explainable AI methods could also help visualize which parts of the logo influenced the classification decision, thereby improving transparency and trust in the system. Furthermore, deploying the system as a web-based or mobile application with real-time monitoring dashboards would allow organizations to track logo misuse across digital media more efficiently. With these improvements, the system can evolve into a more intelligent, scalable, and user-friendly platform for protecting brand identity and detecting counterfeit logos in large-scale digital environments.

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