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Deep Learning Algorithm for Hand Motion Pattern Recognition

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ABSTRACT :

Computers are employed in many different sectors and are an integral part of our daily lives. Conventional input devices, such as a mouse and keyboard, enable human-computer interaction.

When used effectively, hand gestures can facilitate and expedite human-computer interaction. Individual differences exist in the direction and form of gestures. Non-linearity is thus present in this issue. This research suggests a method to interpret the picture and anticipate the hand motions using a Convolution Neural Network (CNN), a Deep Learning Algorithm. This essay demonstrates how to recognize five hand motions used in American Sign Language. Modules for pre-processing, feature extraction, model training and testing, and sign-to-text translation are included in the suggested system. In order to improve recognition accuracy, several CNN architectures, such as VGG19, are also used. Pre-processing methods, such as greyscale and scaling, were created and evaluated using our dataset.

Keywords: Hand Gestures, Human-Computer Interaction, Deep Learning, Convolutional Neural Network (CNN), Sign Language Recognition

1. INTRODUCTION:

Using machine learning techniques, the identification of signals using hand gestures has become a crucial field with many applications. Hand gestures create a more smooth and interesting user experience by giving users a natural and intuitive method to interact with technology. When using conventional input devices like keyboards and mouse is difficult or impossible, this type of contact is especially helpful. The capacity of machines to precisely read and comprehend hand gestures has greatly improved because to developments in machine learning, particularly deep learning. With an emphasis on sign language, this study investigates the use of convolutional neural networks (CNN) for hand gesture recognition in order to provide a more inclusive and accessible technology environment. The potential of understanding hand gestures to transform communication for people with impairments is one of its most exciting features. It might be difficult for persons with speech problems or restricted mobility to communicate using traditional techniques. We can close the communication gap and provide these people a strong means of self-expression by creating tools that can properly understand sign language. This has significant ramifications for raising their standard of living and facilitating more diverse interactions in a variety of contexts, such as private correspondence and public services.
The main focus of this work is on hand gesture recognition and interpretation utilizing deep learning techniques. Our method is based on Convolutional Neural Networks (CNNs), which are well-known for their effectiveness in image processing applications. Because CNNs can automatically and adaptively learn the spatial hierarchies of features from input pictures, they are especially well-suited for this purpose. This makes it possible for the system to manage the non-linear changes in hand motions that result from individual variances in movement, form, and orientation. The goal of this study is to identify five distinct American Sign Language (ASL) hand motions. Because ASL is a complicated tongue with its own syntax and syntax, effectively interpreting its signals necessitates advanced processing and analysis. The CNN model is trained and tested, initial processing and recognition of features are included, and identified motions are translated into text in the proposed system. Every one of these components is essential to maintaining the precision and dependability of the gesture detection system. Grey scaling and picture resizing are two crucial pre-processing methods for getting the data ready for the CNN. To improve performance and accuracy, these strategies aid in standardizing the provided data and lowering computing complexity. We may expedite the training process and strengthen the model's capacity for extrapolating from the data used to train to new, unseen cases by converting the input photos into a uniform format.

During the training phase, the pre-processed pictures are fed into CNN, and the network's parameters are adjusted to decrease gesture recognition error. A substantial dataset of annotated pictures is needed for this iterative process to make sure the model picks up the proper correlations between input visuals and the movements that go along with them. We may raise the model's accuracy and resilience by utilizing strategies like data augmentation and utilizing a well selected dataset. Comparably essential is model testing, which enables us to assess how well the trained CNN performs with fresh data. During this stage, the model's recall, accuracy, precision, and other pertinent metrics are measured to make sure it functions properly in a variety of scenarios. Any flaws or opportunities for development may then be fixed by adding further training or fine-tuning the model's architecture, as shown by the analysis of the outcomes. This study examines many CNN designs, including the deep network VGG19, which is well-known for its efficiency in image classification applications. The design of VGG19, which uses tiny convolutional filters and has depth, makes it ideal for capturing the fine features of hand motions. Our goal is to determine the ideal configuration for our gesture detection system by testing various architectures and setups.

The ultimate objective of this study is to create a system that reliably interprets and recognizes hand motions, enabling communications through sign language. This technology may be included into a number of applications, such as interactive systems for smart surroundings or assistive technologies for people with impairments. We can aid in the creation of more logical and natural human-computer interactions by improving gesture detection technology. In conclusion, a major advancement in the field of interaction between people and computers has been made with the application of algorithms using deep learning, especially CNNs, for hand gesture detection. This study opens the door for new developments and applications by proving that precisely interpreting hand gestures through the use of sophisticated machine learning algorithms is both feasible and useful. We can open up new channels for communication and engagement by carrying out more research and development of these methods, which will ultimately improve how we employ technology in every aspect of our lives.

2. LITERATURE SURVEY

Deepika et al. proposed that photos and videos may be processed [1] to understand and extract information using computer vision and machine learning. This work investigates the recognition of hand gestures using computer vision and machine learning, as they are the most widely utilized form of everyday communication. The suggested approach aims to show how to use Python and OpenCV to use computer vision and machine learning algorithms for motion identification. These enable us to differentiate between hand motions done in midair. The output screen shows the output, often known as the computer webcam stream. Jayanti et al. due to its promise to enable natural human-computer interaction, machine learning approaches for hand gesture recognition have gained importance. The use of machine learning, in particular deep learning techniques [2], for precise hand gesture interpretation and subsequent identification of related indicators is investigated in this work. Our approach uses convolutional neural networks (CNNs) to gather characteristics and categorize motions from massive datasets of hand gesture photos. By offering a reliable and effective way to comprehend and convert hand gestures into usable instructions or messages, the suggested system seeks to eliminate communication gaps. We show via thorough testing and analysis that our method is dependable and efficient in accurately identifying a large variety of indications. Through the development of interactive interfaces, accessibility solutions, and assistive technologies, this study opens up new possibilities for smooth hand gesture engagement and communication in a variety of applications.

Pavlovic et al. proposed that hand gestures are a natural way to communicate, and improving human-computer interaction (HCI) may be greatly aided by understanding how they are visually interpreted. Using computer vision, machine learning, and other techniques, this paper looks at the most recent developments in hand gesture recognition and interpretation for HCI applications [3]. We examine a range of strategies, examining their benefits, drawbacks, and uses. These strategies include deep learning-based methods and conventional handmade feature-based methods. In addition, we talk about issues like illumination, occlusion, and real-time processing demands. The paper also identifies new directions in gesture detection accuracy and robustness, including multimodal fusion and attention processes. This paper attempts to offer a thorough overview of the area and propose potential paths for the advancement of gesture-based HCI systems by combining ideas from current research. Abhishek et al. for those who are hard of hearing, sign language is an essential means of communication; yet, there are obstacles in using sign language in traditional communication settings. This study presents a glove-based hand movement recognition system that translates American Sign Language (ASL) movements into text or voice by using capacitive touch sensors. Sensors included within the glove track finger locations and motions to capture the complex hand signals used in ASL. In order to identify certain indicators, the collected data is analyzed using machine learning methods like support vector machines (SVMs) and convolutional neural networks (CNNs). The suggested solution delivers real-time ASL gesture detection by fusing machine learning [4] with capacitive touch technology, opening up interaction among the hearing population and the hearing challenged.

Rautaray et al. because of its versatility and ease of use, vision-based detection of hand gestures has become a popular technique for improving human-computer interaction (HCI). An overview of the most recent methods and developments in vision-based hand movement identification for HCI applications is given in this review. We examine many methodologies [5], evaluating their benefits, drawbacks, and potential uses. These include multimodal fusion tactics, deep learning-based approaches, and conventional computer vision methods. We also go over assessment measures and datasets that are often utilized in gesture recognition studies. We also emphasize issues such lighting variations, occlusion, and the need for real-time processing, along with possible fixes and future research areas. This review attempts to give a thorough overview of the area by combining ideas from current literature, assisting both researchers and practitioners in creating more effective and efficient gesture-based systems. Erden et al. describes a brand-new finger gesture-based remote-control technique that makes use of a combination of a camera with infrared (IR) sensors. Users can communicate with electronic gadgets using the suggested approach by making hand gestures that are recorded by the device's camera and identified using infrared sensors. While the camera records intricate hand motions for identification, the infrared sensors pick up hand movements inside designated zones. Convolutional neural networks (CNNs) and other machine learning techniques [6] are used to categorize and decipher the motions and convert them into commands for controlling the gadget. Robustness and adaptability are provided by the combination of infrared cameras and a camera, enabling precise gesture detection in a range of situations and lighting conditions. The system's usefulness and dependability in remotely operating electrical equipment using hand gestures are demonstrated by the experimental findings.

Shukla et al. in order to precisely understand and categorize hand movements, this study presents a hand gesture identification system that integrates computer vision methods with machine learning algorithms. The technique makes use of depth-sensing cameras to record three-dimensional (3D) information regarding hand gestures, allowing for reliable identification even against complicated backdrops and difficult lighting situations. A convolutional neural network (CNN) model [7] is trained using features that are retrieved from the depth data, such as hand form, motion direction, and finger articulations. With great accuracy, the trained CNN can identify a large variety of hand movements. The usefulness of the suggested strategy is shown by experimental findings in a variety of applications, such as virtual reality control, human-computer interface, and sign language recognition. Swati et al. proposed that people who are stupid or deaf use gestures to communicate. Several applications utilizing computer vision, machine learning, gesture recognition, etc. have been created. This study presents a basic gesture recognition technique. Here, Python libraries like Numpy and Opencv are utilized. The method entails recording live gestures and utilizing OpenCV tools [8] to recognize them. To distinguish between various gestures, parameters like the area proportion and convexity flaws are taken into consideration. Additionally, text messages will be shown by the system, and the various movements will be spoken over by an audio file. There is a feature that allows motions to be identified for amusement. People who are blind may find this useful for enjoyment purposes like listening to the radio, playing music, or watching the news.

3. METHODOLOGY

The suggested real-time hand gesture detection system makes use of OpenCV's strong points to provide dependable, low-latency performance. An freely available computer vision framework called OpenCV offers a full range of image processing technologies that make it possible to recognize and track hand motions with efficiency. Real-time operation is the goal of this system, which records footage received from a camera, processes the frames to recognize hand movements, and then interprets these gestures to carry out predetermined tasks. The system's ability to react instantly is its main priority, which makes it ideal for applications that need quick responses, such interactive gaming, sign language translation, and other types of human-computer interaction. The core of the system consists of many image processing methods made possible by OpenCV. The first stage is to record video frames and apply preprocessing to them in order to improve hand movement visibility. To separate the palm of your hand from the backdrop, methods including contour detection, thresholding, and background removal are used. The hand is recognized, and the system follows its motions across a series of frames. Maintaining a steady and precise identification process even when the hand moves swiftly or changes orientation depends on this ongoing monitoring. The utilization of OpenCV's optimized algorithms guarantees the effective execution of these tasks, hence reducing computing overhead and delay.

In this system, powerful classification algorithms are integrated to accomplish gesture recognition. These algorithms use the hand's preprocessed photos to recognize particular motions. In this categorization process, machine learning models—especially those trained on a variety of hand gestures—are essential. Through the application of both conventional computer vision methods and machine learning, the system is able to recognize various motions with high accuracy in real-time. Applications such as sign language translation, where accurate and prompt hand sign recognition is necessary to promote successful communication, depend on this capacity. The suggested system's emphasis on real-time adaptability is one of its most notable characteristics. Low-latency processing is given top priority in the design to guarantee nearly immediate gesture recognition and interpretation. With interactive apps, where delays can ruin the user experience, responsiveness is especially crucial. For example, players in virtual reality or gaming settings depend on prompt input from the system to stay in control and immersed. In the case of sign language interpreting, the system's seamless processing and interpretation of motions can greatly improve the flow of communication.

The suggested approach also prioritizes economy of resources and simplicity. The solution leverages a mature and highly efficient library by using OpenCV, which eliminates the need for significant bespoke work. As a result, the system may be used and implemented on a variety of hardware platforms, ranging from powerful desktop computers to more limited gadgets like smartphones and embedded systems. The objective is to provide a solution with broad application across many use cases and settings, while simultaneously being lightweight, flexible, and powerful. The technology, which prioritizes speed and simplicity, claims to allow for dynamic and intuitive hand gesture management of digital interfaces, creating new opportunities for user engagement across a range of fields.

4. CONVOLUTIONAL NEURAL NETWORKS

Machine learning for hand gesture recognition requires carefully crafting gesture sets and gathering information via picture or video capture. For consistent effects, lighting, backgrounds, and camera angles must all be consistent. A trained dataset is created by labeling gathered data appropriately. Resizing, normalizing, and augmenting data are examples of preprocessing techniques that improve data appropriateness for model training. Organizing test, validation, and training sets separately makes it possible to evaluate models effectively. Lastly, precise gesture identification and model learning are facilitated by extracting features from preprocessed data. By employing machine learning techniques, this iterative approach guarantees the resilience and efficacy of hand gesture recognition. In order to use machine learning algorithms [9] for hand gesture recognition, preprocessing is essential. Initially, preprocessing is done on acquired data to define format, size, and quality. This data is frequently in the form of photos or videos. This include converting films to frames, scaling photos to a standard quality, and making sure that backdrops and lighting are constant. In order to help with model convergence, normalization techniques are used to normalize pixel values. Furthermore, data augmentation reduces overfitting by increasing dataset variety by operations like rotation, flipping, or introducing noise. Techniques for background removal may be used to separate hand areas, which will make gesture extraction easier. Removing unnecessary background noise enhances the quality of data even further. Preprocessing encourages reliable model training and precise hand gesture identification by optimizing data compatibility with machine learning techniques.

A crucial step in machine learning-based hand gesture detection is feature extraction. The procedure involves extracting relevant information from previously processed data in order to accurately depict gestures. Methods include a variety of approaches: Features that are handcrafted, such as HOG or LBP, contain data like texture, color, or shape. CNNs and RNNs are examples of deep learning techniques that automatically extract discriminative features from unprocessed data. Skeletal-based representations are made possible by depth sensors, which record joint angles or locations. Trajectories and velocities of dynamic gesture motions are captured by temporal characteristics. Statistics that reveal information about the distribution of data include variance and mean. The choice of approach depends on variables including processing efficiency and data properties. Robust representation is ensured by optimal feature extraction, which makes it easier for machine learning frameworks to recognize hand motions accurately. Deep Learning has shown to be an extremely potent technique over the last two decades because to its capacity to manage massive volumes of data. Particularly in pattern recognition, the usage of hidden layers has overtaken interest in more conventional methods. Convolutional Neural Networks are among the most often used deep neural networks.

Researchers have battled to create a system that can comprehend visual input since the 1950s, when artificial intelligence was still in its infancy. In the years that followed, this area of study became known as computer vision. When a team of University of Toronto researchers created an AI model in 2012 that outperformed the most advanced picture identification algorithms and by a significant margin computer vision saw a quantum leap. With an astounding 85% accuracy rate, the artificial intelligence system dubbed Alex Net after its primary developer, Alex Krizhevsky won the 2012 ImageNet vision system competition. The test's runner-up received a respectable 74 percent. Convolutional neural networks, a unique class of neural networks that closely resemble human vision, are the brains behind Alex-Net. CNNs [10] are now a crucial component of a number of computer vision applications and, as such, are taught in computer vision courses. Now, let's examine how CNNs function. Around the 1980s, CNNs were first created and put to use. At the time, a CNN's maximum capability was handwritten digit recognition. It was primarily used to read pin numbers, zip codes, and other data in the postal industry. The most crucial thing to keep in mind about a deep learning algorithm is that it needs a lot of processing power and a lot of data to train. This was a significant disadvantage for CNNs at the time, which prevented them from breaking into the machine learning space and keeping them confined to the postal industry.

Alex Krizhevsky came to the conclusion in 2012 that the multi-layered neural network-based deep learning branch needed to be revived. Researchers were able to resurrect CNNs because to the availability of massive datasets more precisely, ImageNet datasets containing millions of annotated pictures and an abundance of processing power. The class known as convolutional neural networks (CNN/Conv Net) is most frequently used to assess visual images. Nowadays, matrix multiplications come to mind when we think of neural networks, although Conv Net does not operate like that. It makes use of a unique method known as convolution. In the language of mathematics, convolution is an operation on two values that yields a third one that describes the transformation of one's shape by the other. However, in order to comprehend what a CNN is and how it functions, we don't really need to get beyond the mathematical portion. In summary, the ConvNet's job is to simplify the pictures without sacrificing any of the essential characteristics needed to provide a reliable forecast.

Let's go over the fundamentals first, such as what an image is and how it is displayed, before moving on to how CNN operates. An image in grayscale is the same as an RGB image but has a single plane, while an RGB image is nothing more than a matrix of pixel values with three planes. Check out this picture to learn more. Artificial neurons are arranged in numerous layers to form convolutional neural networks. Artificial neurons are mathematical functions that compute the weighted sum of many inputs and output an activation value. They are an approximate mimic of their biological counterparts. Each layer in a ConvNet creates a number of activation functions upon receiving an image input, which are then forwarded to the subsequent layer. Typically, the initial layer captures fundamental properties like edges that are diagonal or horizontal. The following layer receives this output and uses it to identify more intricate characteristics like combinational edges and corners. Deeper inside the network, it can recognize even more intricate aspects like faces, objects, and so on. The classification layer produces a series of confidence scores (numbers between 0 and 1) indicating the likelihood that a picture belongs to a "class" based on the activated map of the final convolution layer. For example, the output of the last layer of a ConvNet that can identify cats, dogs, and horses is the likelihood that any of those reptiles are present in the input image. The Pooling layer is in charge of shrinking the dimension of the Convolved Feature, just like the Convolutional Layer does. This reduces the dimensionality of the data, which in turn lowers the computer power needed to analyze it. Average pooling and maximum pooling are the two forms of pooling. My sole experience to far has been with Max Pooling, and thus far, no issues have arisen. Therefore, in max pooling, we determine a pixel's maximum value from a section of the picture that the kernel covers. Additionally, max pooling serves as a noise suppressant. It reduces the dimensionality, conducts de-noising, and completely eliminates the noisy activations.

An annual computer vision competition is called the ImageNet Large Scale Visual Classification Challenge. Teams engage on two tasks a year. The first is object localization, which is the process of identifying items in a picture from 200 classifications. The second task is picture classification, which involves labeling each image with one of a thousand categories. In 2014, Karen Simonyan and Andrew Zisserman from Oxford University's Visual Geometry Group Lab suggested VGG 16 in their work, "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION." In the 2014 ILSVRC competition, this model took first and second place in the aforementioned categories. Using the 14 million photos from 1000 classes in the ImageNet dataset, this model obtains 92.7% top-5 test accuracy. The ImageNet dataset comprises 224*224 fixed-size pictures with RGB channels. Thus, our input is a tensor of (224, 224, 3). After processing the input picture, this model produces a vector with 1000 values. The classification rate for the associated class is represented by this vector. Assume for the moment that we have a model that indicates that a picture belongs to class 0 with probability.1, class 1 with probability 0.05, class 2 with probability 0.05, class 3 with probability 0.03, class 780 with risk 0.72, class 999 with probability 0.05, and all other classes with 0. As a result, the classification vector in this case is: The network receives an image with dimensions of (224, 224, 3). The 64 channels in the first pair of layers have the same padding and a 3*3 filter size. Following a max pool layer with stride (2, 2) are two layers with convolution layers with filter sizes of 256 and 3, respectively. A maximum pooling layer of stride (2, 2)—the same as the preceding layer—follows this. Next, there are two convolution layers with 256 and 3 filter sizes. A max pool layer and two sets of three convolution layers follow. Each has the same padding and 512 filters with a size of (3, 3). Next, this picture is sent to two convolution layers' stack. Following the convolution and the maximum pooling layer stack, we were left with a (7, 7, 512) feature map. In order to create a (1, 25088) feature vector, we flatten this result. There are three fully connected layers after this. The first layer uses the last feature vector as input and outputs a vector with size (1, 4096). The second layer likewise produces a vector with the same size (1, 4096), but the third layer produces 1000 channels for 1000 classes of the ILSVRC challenge. The output of the third fully connected layer is then passed to the softmax layer, which normalizes the classification vector. following the top five categorization vector categories for assessment. ReLU is used by all hidden layers as their activation function.

5. RESULTS

To guarantee accuracy and dependability, the performance of the suggested hand gesture detection system was assessed using a wide range of indicators. Thirty percent of the dataset was utilized for testing, while the remaining seventy percent was used to teach the models. In machine learning, this division is typical procedure to guarantee that the predictive algorithm is trained on an adequate quantity of data while keeping a distinct subset to assess its effectiveness on unseen cases. This technique aids in evaluating the model's capacity for generalization outside of the training set. Predictive accuracy serves as this work's main assessment criterion. In classification tasks, accuracy is an important indicator since it shows the percentage of properly predicted examples out of all the occurrences. The ratio of the variety of accurate forecasts to the The total amount of predictions made is the definition of accuracy in mathematics. It offers a clear indicator of the overall success rate of the model. High accuracy shows that the model is correctly classifying the data and successfully identifying patterns in the data.

While this statistic provides a clear picture of the model's performance, other metrics should also be taken into account to provide a more complete picture. Because of this, we also looked at a matrix of confusion, which offers a more thorough analysis of the predictions made by the model. One of the core instruments in predictive analysis is the confusion matrix. N is the number of labels for each class in the classification task, and the matrix is N x N. For a given set of actual and expected classes, the number of instances is represented by each cell in the matrix. The counts of accurate predictions are represented by the central diagonal of the matrix, whereas the counts of incorrect classifications are represented by the off-diagonal columns. The ratio of actual positive predictions to all of the model's positive predictions is known as precision. It shows how well the model detects positive events. A high accuracy indicates a low number of false positive mistakes made by the model. Conversely, recall is the proportion of real positive cases to genuine positive forecasts. It gauges how well the model is able to extract all pertinent examples from the dataset. A high recall rate indicates that the majority of positive examples can be identified by the model.

A simple measure that balances accuracy and recall is the F1 score, which is the balanced average of the two. Because it makes sure that neither recall nor accuracy are disproportionately favored, it is especially helpful in situations when there is an unequal class distribution. Using the Enthought Canopy platform, we evaluated six alternative algorithms on the same dataset. This made it possible for us to evaluate the effectiveness of several strategies and determine which one was best for the recognition of hand gestures. The outcomes were examined in terms of memory, accuracy, precision, and F1 score, offering a thorough assessment of the functionality of each method. Each algorithm's confusion matrix provided information about the different kinds of mistakes that were being made. For example, it can be a sign that the model needs to be improved or that more training data is needed if particular motions were often confused with one another. We were able to identify particular flaws in the model and fix them by fine-tuning the training procedure or making changes to the algorithm by looking at the confusion matrix.

Overall, the findings showed that the suggested system could recognize hand gestures in real time with high accuracy by utilizing OpenCV and deep learning techniques. The system's accuracy and dependability were demonstrated by the performance measures, which made it appropriate for a range of uses including interactive gaming, human-computer interaction, and sign language translation. Future improvements and advances will be guided by the thorough study that the confusion matrix and other metrics offered, which made sure that the system's strengths and places for improvement were known. In conclusion, a comprehensive analysis of the suggested hand gesture recognition system's performance was given by measuring its accuracy, confusion matrix, and other relevant metrics. Real-time hand gesture detection using Api and deep learning is shown to be successful, as demonstrated by the high accuracy and positive performance metrics. The system may now be implemented in a variety of real-world settings since this thorough assessment approach guarantees that it not only satisfies but also surpasses the criteria for interactive applications.

CONCLUSION :

Human-computer interaction has advanced significantly with the creation and assessment of the suggested real-time hand gesture detection system that makes use of deep learning algorithms and OpenCV. The system efficiently recognizes, tracks, and classifies hand movements with high precision and low latency by utilizing powerful Convolutional Neural Networks (CNNs) and strong image processing techniques. This makes it appropriate for applications like interactive gaming, sign language translation, and other changing digital interfaces. The data was split into training and testing sets to allow for a complete examination of the model's generalize capabilities. The system's usefulness was also thoroughly evaluated using performance measures including accuracy, precision, recall, and the F1 score. The model's predicted dependability was further clarified by the confusion matrix, which also indicated areas that may be improved. Overall, the suggested system not only achieves strong resource efficiency and real-time responsiveness, but it also holds promise for improving digital interactions' accessibility and intuitiveness. It provides a strong tool for a range of interactive applications and makes a substantial contribution to the development of adaptive technology and natural interfaces for humans and machines.

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