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Jul 23, 2024

Plagiarism Scan Report

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Characters:4910	Words:767
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Excluded URL	None

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3.4 Feature Extraction of Spatial and Temporal Features from Images The proposed method in this article consists of three main steps. In the first step, each frame of the video is preprocessed, and the edges of the frames are extracted. Then, a CNN model is applied to the resulting image for spatial feature extraction, and two LSTM models are applied to extract temporal features. LSTMs are RNN-based neural network models that can preserve the sequence of events. The proposed method in this research is an improved version of the model presented in citation. The overall process of the proposed method is illustrated in Figure 2. According to Figure 2, this project focuses on investigating the application of edge detection methods to improve the detection of surgical tools in laparoscopic images. As mentioned in previous sections, this article is based on reference [16]. Therefore, the innovation of our article lies in using edge detection to improve the performance of the model presented in reference [16]. Based on the process of edge detection, feature extraction, and object recognition outlined in this article, the feature extraction and object recognition section is based on the model presented in reference [16]. Therefore, the extraction process includes two steps: extracting temporal features based on the LSTM algorithm and extracting spatial features based on the CNN algorithm. In this study, two advanced CNN models named VGG-16 and ResNet-50 were used on a dataset to train for the identification of surgical tools and phases. The VGG-16 model consists of five convolutional blocks and three fully connected layers that were replaced with new layers for tool and surgical phase detection. The ResNet-50 model underwent similar modifications. For image representation, 4096-dimensional or 2048-dimensional feature vectors from the VGG-16 and ResNet-50 models were used as feature extractors and then forwarded to the LSTM model. Endoscopic videos contain both static and sequential information. Two LSTM units named LSTM-clip and LSTM-video were introduced to capture the presence of tools in sequential images. LSTM-clip predicts the presence of tools in the target frame based on a sequence of unlabeled frames. Training videos are divided into short clips, feature vectors are extracted using CNN for each clip, and then sent to LSTM-clip. Subsequently, VLSTM-clip with dimension C is generated for tool classification. LSTM-video is utilized to incorporate sequential information across consecutive clips of a video. The feature vector sequences produced by LSTM-clip are input into the LSTM-video model, which has a fully connected layer for tool classification. 3.5 Evaluation Metrics The evaluation metrics used in this article include: The Average Precision (AP) metric was used as an evaluation metric for the tool classification task. This metric is defined as the area under the precision-recall curve and can be calculated based on formula 1 [16]: Apt=0tPt.d[Rt] (1) where Ptis the precision and Rtis the recall of tool t as a function of confidence threshold. Other metrics such as accuracy, precision, recall, and ROC curve are also provided. 4. Results This section presents the experimental results. First, the evaluation process is described, followed by the results. In this article, the results are presented based on multi-class scenarios, detection of surgical tool types based on different edge detection methods. For the multi-class scenario (4 classes), the detection of grasper, hook, scissor, and clipper tools is considered. In this article, to evaluate the proposed method based on the process of evaluating machine learning models, the data was divided into two categories: training and testing. The holdout method was used to split the data into training and testing sets. Therefore, 70% of the data was considered for training and 30% for testing. Table 2 shows the results of the algorithms used based on evaluation metrics. According to Table 2, the Prewitt filter outperformed other methods in terms of performance. This indicates that the Prewitt filter extracts more useful information from the image and improves the model's performance by eliminating less useful information. In Figure 3, the ROC curve for the overall performance of the filters in tool detection is presented. It is observed that a higher area under the curve (AUC) in the ROC curve indicates better model performance. In this case, based on Table 2 and Figure 3, the Prewitt method had better performance in detecting the presence or absence of surgical tools in the image compared to other methods. The presence of a surgical tool refers to whether a specific surgical tool is present in the current frame or not, indicating a binary classification by the model. The last row in the table ranks each model, with lower numbers indicating better performance and ranking.

Sources