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Comparing the Performance of Fully Convolutional Networks and Support Vector Machines for Liver Segmentation and Classification in Magnetic Resonance Imaging (MRI) Images

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Abstract. The Fully Convolutional Network (FCN) and the Support Vector Machine (SVM) are two well-known classifiers that are used for MRI-based novelty liver segmentation classification. This study aims to compare and contrast these two classifiers. To train classifiers using SVM and FCN, twenty samples of liver MRI images were used. Two groups, one using support vector machines (SVMs) and the other using FCNs, were given ten samples each. This study's pretest power is 80%. In MATLAB, FCN has a recognition rate of 97% compared to 86% for SVM. Our statistical study yielded a satisfactory accuracy ratio (P<0.05). Compared to the SVM method, the FCN method achieved superior results on the datasets tested for unique liver segmentation categorization.

A wider field of deep learning includes new methods for liver segmentation, MRI, classification, and fully convolution neural networks (FCNs).

INTRODUCTION

Processing metabolism, synthesizing proteins, and breaking down red blood cells all rely on the liver, a major generator of biochemical's [1]. On a global scale, liver cancer is the sixth most prevalent malignancy. According to 2017 statistics from the World Health Organization, 1040 people in Ethiopia lost their lives to liver cancer [2]. This represents 0.16% of all cancer fatalities nationally. Hepatocellular carcinoma (HCC) and other liver malignancies account for about 700,000 annual fatalities, placing them third among cancers in terms of mortality rate [3]. If the liver isn't doing its job, it could have systemic effects. Contrary to popular belief, the early stages of liver disease often do not manifest with any outward signs of illness. Among adults, hepatocellular carcinoma (HCC) is the most prevalent primary malignant tumor of the liver. Liver metastases account for 25% of all solid organ metastases, which help differentiate between primary and metastatic malignancies. Consequently, prompt diagnosis is crucial [4]. An MRI investigation found that the suggested strategy greatly improved the accuracy of liver segmentation [5]. Deep learning techniques, such as the FCN classifier, are used to categorize liver segments. There are a number of ways to categorize and utilize images and videos [6]. Medical image analysis is one such area. Recently, there has been a plethora of research on hepatic classifiers that use deep learning and machine learning to segment the liver. Google Scholar has 1,780 articles indexed from 92 publications in IEEE Explore. Due of its 89% accuracy rate in predicting outcomes using the FCN approach, disease deep learning systems have been extensively studied in surveys. Even while X-ray or CT scans may show bone, they cannot glean medical information about other tissues or bones [7]. Separation, preparation, identification, and classification were the four phases that made up the system [8]. The researchers in this study relied on magnetic resonance imaging (MRI) scans for their data because of the high regard in which this imaging method is held. Their high definition MRI pictures reveal more details in the tissue and bone, which is why they are so popular. By using edge detection, the training set is chosen [6]. The SVM classifier is used to segment the picture's 3D volume. There is a 90% success rate when following these procedures

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[7]. Several fields have benefited from our university's commitment to doing high-quality, evidence-based research [9].

Classifying liver grades is made challenging by the poor accuracy values of the current methodologies. Liver tissue may be difficult to precisely categorize, and the difficulty increases with the passage of time. The primary objective of this research is to address the previously identified issue by using the FCN classifier. As may be seen from references [1] through [10], our team members have extensive experience doing research in a wide range of fields.

MATERIALS AND METHODS

The Saveetha School of Engineering in the Indian state of Tamil Nadu is associated with SIMATS and offers courses in electrical and communication engineering; it was there that the project's research was conducted. The detection of bone tumors requires a total of twenty samples, ten from each group. Data from prior clinical studies was used on Clinical.com to establish the sample size. A criterion of 0.05 percent, a confidence interval of 95%, an enrolment ratio of 1, and a G power of 80% were all established. The data was generated by means of the Mat lab program [8].

In order to verify the present and recommended methodologies, a dataset of 20 low resolution liver CT scans reduced to 192 258 pixels was inputted into the SPSS IBM software. The dataset was then converted to MSEXCEL for statistical analysis. For training with these datasets, a screen with sufficient resolution is required. You will need a 7th Generation machine, an i5, 4 GB of RAM, and 500 GB of hard drive space in order to train on these datasets. A fully functional version of MATLAB (2019) with all the features required by the tool library is also required. The research relied on data derived from liver MRIs (magnetic resonance imaging). If you are planning to assess these datasets, here are some steps to take into account: the first step is to pre-process the original image using an image enhancement technique; the second step is to segment the image; the third step is to use coding methods for image classification and identification; and the fourth step is to identify the affected area. Twenty MRI scans of the liver served as independent factors in this study, with the validity of the inquiry serving as the dependent variable. The FCN classifier and other deep learning algorithms are used by this recommendation system to provide recommendations. This FCN classifier excelled at image recognition. An FCN consists of an input layer, a convolution layer, and a pooling layer. The input layer is the foundation of any network design. The FCN classifier does not have very dense layers. The task at hand is really completed by use of eleven distinct convolutions.

The FCN model is built up from individual convolution blocks, which each include two-dimensional convolution layers and a regularization step. Throttling is used to expedite convergence and prevent over fitting. Activation layers are used to include non-linearity even further. The input batch size is usually automatically added by Keas. It is not necessary to declare dimensions in the input layer; FCN automatically includes them. The FCNs will be entrusted with the categorization responsibility. Thick stacking and one-to-one convolutions are the two primary methods for constructing FC layers.

The 512 × 512 pixel format is used as the input picture, as seen in Figure 1. The procedure's preparation stage does an image enhancement and does a colour conversion before storing the picture. Pixels are converted from black to white or white to black as part of the segmentation process so it can handle 0s and 1s. Identifying and classifying the liver's segments is the last step, which we have already completed. The FCN algorithm does this by using a new method of segment categorization for the human liver.

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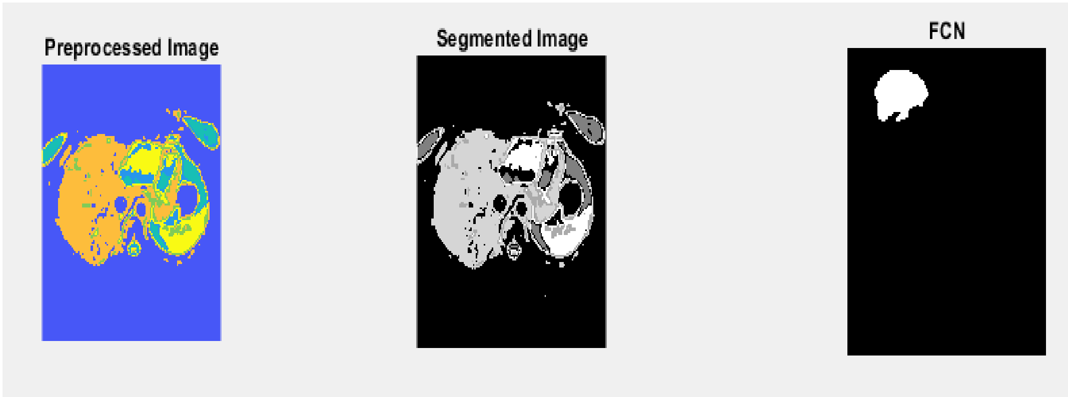

FIGURE. 1. Magnetic resonance imaging (MRI) images used for liver segmentation; dataset input image; and, after pre-processing, the final segmented output picture.

Statistical Analysis

A dataset consisting of 20 low-resolution liver MRI images—down from 192,258 pixels in the lobby—was translated to MSEXCEL (an IBM SPSS tool) in order to evaluate the statistical analysis procedure. The year 19 A sample t test was used, which includes both independent and dependent samples. The 20 separate liver MRI images are the independent factors in this research, whereas accuracy is the dependent variable.

RESULTS

In order to assess statistical analysis tools, a dataset including both existing and proposed methodologies is transferred to Microsoft Excel. The dataset, which is an input from the SPSS IBM software, consists of twenty reduced, low-resolution liver MRI images, each measuring 192 258 pixels. [9] The use of independent samples allowed for the execution of a sample T test. The accuracy level serves as the dependent variable in this study, with the 20 liver MRI pictures serving as the independent factors. A bar chart comparing the different degrees of accuracy is shown in Figure 3. (some algorithms that fall under this category include SVM and FCN) With 97% accuracy, FCN significantly outperforms SVM's 86%. Having said that, it seems that the two approaches' standard deviation ranges are almost identical.

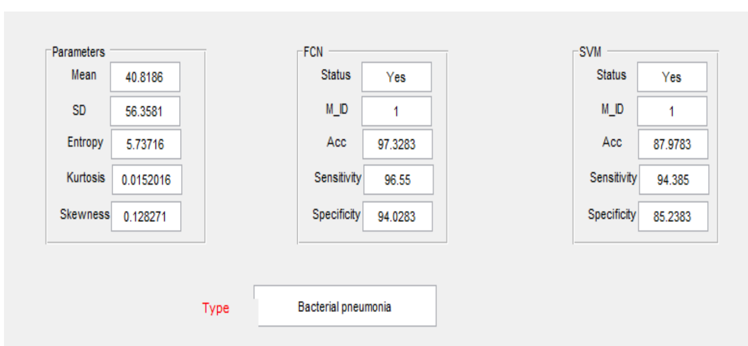

FIGURE. 2. The findings are shown in the output after comparing the accuracy of the FCN classifier with the SVM classifier. Compared to SVM's greatest performance of 87%, CNN's accuracy rate is 97%.

The comparison of accuracy levels is shown in Figure 3, which can be seen here. (algorithms such as SVM and FCN are examples) A much greater accuracy of 97% (1%), as produced by FCN, is achieved in comparison to SVM's 86% (1%). On the other hand, it seems that the two methods are rather comparable with respect to the standard deviation's range distribution.

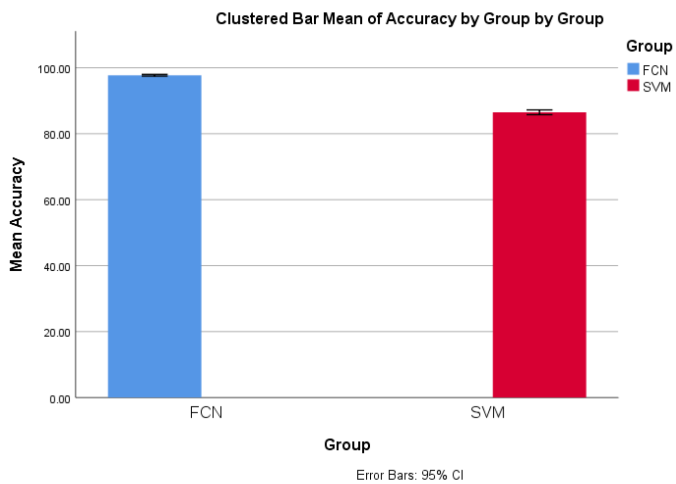

FIGURE. 3. Here, we compare the FCN method with the SVM algorithm, looking at how well each one performs on average. While support vector machines (SVMs) only manage 86% accuracy on average, FCNs reach 97%. On the X-axis, we can see the comparison between the FCN method and the SVM algorithm. Detection accuracy, on average, has to be between zero and one standard deviation.

Table 1 displays the results of a t-test that distinguished between the FCN algorithm and the SVM approach. A lower mean value (86.4900) was found for the SVM classifier, but a higher mean value (97.7240) was found for the FCN classifier. The standard deviations of the two are significantly different from one another. In contrast to FCN's 1.00820, SVM's worth is a meagre 0.36515.

Figure 1: T-test When looking at the mean values of the FCN and SVM classifiers, we find that the former has a greater value (97.7240) while the latter has a lower value (86.4900). They don't have the same standard deviations. In contrast to SVM's 1.00820, FCN's is 0.36515.

	Groups	N	Mean	Std. Deviation	Std. n Error Mean
ACCURACY	FCN	10	97.7240	0.36515	0.11547
	SVM	10	86.4900	1.00820	0.31882

Table 2 displays the results of a t-test that was administered to both groups using an independent sample. The test yielded the following conclusions: (t=33.130) for accuracy and (Mean Difference=11.23400) for the mean difference. There was also a difference in the standard error of (0.86916), according to the test findings. With a mean difference of 11.23400, the distinctions between these two distinct groups are discernible.

FIGURE 2. Using a T-test on independent samples, we could see that both groups were accurate (t = 33.130), with a mean difference of (11.234000) and a standard error difference of 0.3309, which was the same as before. The fact that the mean difference is 11.23400 shows that there is a statistically significant disparity between the two groups. (P 0.05).

Leven's Test For Equality of Variance				t-test for Equality of Variance					95% Confidence Interval of the difference	
Accuracy		F	sig.	t	dif	Sig (2-tailed)	Mean diff	Std .Error Difference	lower	upper
	Equal Variance assumed	9.195	0.007	33.130	18	0.000	11.23400	0.33909	10.52160	11.94640
	Equal Variance assumed			33.130	11.321	0.000	11.23400	0.33909	10.49025	11.98885

DISCUSSION

Here, the FCN classifier beat the SVM classifier with a 97% classification accuracy (p0.05). The effectiveness of FCN and SVM in liver segmentation was investigated in this work using the Kaggle dataset. Multiple variables indicating the kind of liver disease and various percentages of healthy and ill people are included in the dataset. In order to partition the liver and identify lesions, Avi Ben Cohen suggested a comprehensive network. In this investigation, CT scans were used with the intention of detecting and categorizing the liver. They reached an accuracy level of 92% when using the FCN classifier. She used a support vector machine (SVM)-based classifier in conjunction with feature difference and soft computational approaches to automate the segmentation and classification of liver cancers from CT images. Using a three-stage CAD approach, the researchers in this work achieved an accuracy level of 90% [10]. Support vector machines (SVMs) were proposed by Mallikarjun Kesaratti as a means of liver partitioning and classification. The investigation was carried out using CT scans as the input photographs. A combination of the GLDM and Pseudo Zenerike feature sets allows us to achieve an accuracy of 88% in this scenario [1]. Even though their dataset was imbalanced, Zhou et al. were able to get an 81% sensitivity rate [4] by included 52 healthy photos and 69 images with liver illness. We can see that the FCN classifier gives the best accuracy by comparing it to the SVM classifier. One of the minor drawbacks of the FCN classifier is the extra calculation time required for training.

CONCLUSION

In order to find out how effectively the liver segmentation classifier works, this study compares FCN with SVM on a kaggle dataset. According to the statistics, the FCN technique that relies on deep learning achieves an astounding 97% performance accuracy, while the SVM method only manages 86%. In comparison, the SVM method's accuracy falls short at 86%.

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REFERENCES

1. A. Rajasekar and Senior Lecturer, Department of Periodontics, Saveetha Dental College and Hospitals, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, 600077, India., “Assessment of periodontal status among post menopausal women: A retrospective study,” Int. J. Dent. Oral Sci., pp. 1063–1066, Nov. 2020.
2. V. Varadharaj et al., “Antidiabetic and Antioxidant Activity of Green Synthesized Starch Nanoparticles: An In Vitro Study,” J. Cluster Sci., vol. 31, no. 6, pp. 1257–1266, Nov. 2020.
3. S. Rajasekaran, D. Damodharan, K. Gopal, B. Rajesh Kumar, and M. V. De Poures, “Collective influence of 1-decanol addition, injection pressure and EGR on diesel engine characteristics fueled with diesel/LDPE oil blends,” Fuel, vol. 277, p. 118166, Oct. 2020.
4. “Prevalence of angular bone defects in chronic periodontitis patients with and without systemic diseases,” Indian J. Forensic Med. Toxicol., Oct. 2020, doi: 10.37506/ijfmt.v14i4.12487.
5. J. Sabarathinam, A. Rajasekar, and Madhulaxmi M, “Prevalence of furcation involvement among patients with periodontitis: A cross sectional study,” Int. J. Life Sci. Pharma Res., vol. 11, no. SPL3, pp. 1483–1487, Oct. 2020.
6. S. I. Basha et al., “Fumaric acid incorporated Ag/agar-agar hybrid hydrogel: A multifunctional avenue to tackle wound healing,” Mater. Sci. Eng. C Mater. Biol. Appl., vol. 111, p. 110743, Jun. 2020.
7. Preety, R. Anitha, Rajeshkumar, and Lakshmi, “Anti-diabetic activity of silver nanoparticles prepared from cumin oil using alpha amylase inhibitory assay,” Int. J. Life Sci. Pharma Res., vol. 11, no. 2, pp. 1267–1269, Apr. 2020.
8. S. Andavan and V. K. Pagadala, “A study on soil stabilization by addition of fly ash and lime,” Materials Today: Proceedings, vol. 22, pp. 1125–1129, Jan. 2020.
9. G. Anitha, P. Nirmala, S. Ramesh, M. Tamilselvi and G. Ramkumar, "A Novel Data Communication with Security Enhancement using Threat Management Scheme over Wireless Mobile Networks," 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), 2022, pp. 1-6, doi: 10.1109/ACCAI53970.2022.9752584.
10. Kumar, R.V., Vanitha, M., Prabu, R.T. *et al.* Multiband miniaturisefrequency reconfigurable patch antenna using PIN diodes. *Wireless Netw* **28**, 2485–2497 (2022). https://doi.org/10.1007/s11276-022-02946-6