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Liver Cancer Classification With Using Gray-Level Co-Occurrence Matrix Using DL method

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ABSTRACT:

This study analyzes liver segmentation and cancer detection work, with the perspectives of machine learning and deep learning and different image processing techniques from the year 2012 to 2020. The study uses different Bibliometric analysis methods. Methods: The articles on the topic were obtained from one of the most popular databases- Scopus. The year span for the analysis is considered to be from 2012 to 2020. Scopus analyzer facilitates the analysis ofthe databases with different categories such as documents by source, year, and county and so on.

INTRODUCTION:

Liver cancer is the most common cause of death in the world. In order to find liver cancer, you need to figure out what medical images mean adaptive thresholding with a watershed transform is used to make the liver stand out from the other parts of the body [1]. Optimal strategies and the swarm optimization model are some of the methods usedto separate the malignant area of the liver. The data included 225 images from patients with different types of liver cancer. In order to build a big dataset, the Gray Level Matrix, the Local Binary Pattern was used to find features that areimportant. It then gets broken down into different types of cancer using neural network, support vector machine, random forest, and deep neural network classifiers. These include hemangioma, hepatocellular carcinoma. The suggested methods are judged on their sensitivity, specificity, accuracy, and Jaccard index. People who use watershed Gaussian- based deep learning algorithms have found that they can be used to diagnose liver cancer. DNN classifiers were found tobe the best, with an accuracy of 99.25% and a Jaccard index of 0.97 across 300 epochs with a low validation loss of 65.73% of the accuracy [2]. Cancer is the second chief cause of death globally. As per the statistics from World Health Organization(WHO), it was accountable for 8.8 million fatalities in 2015 out of which 788,000 deaths were caused by liver cancer (WHO, 2020). The American Cancer Society has predicted that about 42,810 fresh cases (30,170 in male and 12,640 in female) will be detected and 30,160 people (20,020 male and 10,140 female) will pass away due to primary liver cancerand intra-hepatic bile duct cancer in USA alone in 2020 (ACS, 2020). Liver is largest gland and important metabolic organof human body. Functions of liver are digestion, metabolism and detoxification. Liver cancers are categorized in two parts such as primary and secondary liver cancer depending upon cause of cancer. Primary liver cancer is cancer that instigatesin the tissue of the liver [3]. Primary liver cancer has two types such as Hepatocellular carcinoma and Hemangioma. Hepatocellular carcinoma (HCC), the development of cancer cells in the tissues of the liver, is the most frequent kind ofliver cancer. A liver Hemangioma is made up of a tangle of blood vessels (Bosch et al., 2004). Secondary metastatic livercancer takes place due to spread of cancer from other body part (Ananthakrishnan et al., 2006). An abnormality in the liver causes the change in the liver texture and shape. Exaction and accurate segmentation of liver, its vessels and tumorsis required in the disease diagnosis. However due to the intensity of homogeneity inside liver , shape of liver, low contrast [4], presence of adjacent abdominal organs it becomes challenging task of accurate liver segmentation. Liver diseases can be diagnosed through various medical imaging schemes such as computed tomography (CT), ultrasound (US), Magnetic Resonance Imaging (MRI) etc (Priyadarsini and Selvathi, 2012). Various statistical methods, threshold based methods, fuzzy based methods [5], clustering techniques, neural network models and machine learning based methods have been adopted in the past for the segmentation of the liver region and cancer detection in liver (Campadelli, 2009). Traditional,Machine learning based methods are highly relying on the hand-crafted features which have lower interconnectivity, poor feature representation and correlation |in the raw features [6].

Survey of Liver Segmentation Abdominal CT images consist of various body parts along with liver. It is indispensable to segment the liver part from the CT images so that proper properties of the liver can be extracted. In the past, variousmethods the segmentation of the liver from the abdominal CT images with the help of deep learning algorithms has been employed such as active contour model (Assaf et al.,, 2016), Laplacian mesh optimization (Gabriel et al., 2016), graph cutmethod (Guodong et al., 2015) [7], 3D liver segmentation (Zhang, 2017). Unsupervised deep learning algorithms have attracted more focus for the liver segmentation and have given better performance than the traditional segmentation methods [8] . Unsupervised Deep Adversarial Networks (DAN) along with Weighted Loss Function (WLF) presented . 1.2 Survey of Liver Cancer Detection For the liver cancer detection various texture, shape and gradient based features have

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been extracted with the help of various shallow and deep learning algorithms. A computer aided systems based on auto-covariance texture features presented for the liver cancer detection in raw and non-pre-processed CT images. Co- variance based features are used for the irregularity capturing of the liver texture image. Co-variance based method often suffered from the illumination changes [9], blur, poor contrast, orientation and size of the liver image. Auto-covariance texture features resulted in an accuracy of 81.7% using the (Huang et al., 2004). A particle swarm optimization (PSO) method was employed for the hepatocellular carcinoma detection in liver images. PSO can yield the better solution along with other algorithm and can find the optimal parameters which can give better cancer detection rate. Perhaps, performance of PSO is not guaranteed and it may stuck in the local minima, it needs more iteration for the learning. It was noticed that instance optimization (IO) and SVM given better performance for liver cancer detection (Jiang et al., 2013).

PROPOSED APPROACH:

Primary Database Collection: Worldwide, there are many popular databases, including Scopus, web of science,Google scholar, scimago etc. Scopus is one of the most popular databases amongst these databases. The same is used for the analysis. Different keywords are used for the search outputs a total of 518 number of publication results. Restrictions on country, language etc. is not considered here. This information with the publication is used for the analysis. Fundamental **Keywords:**
Fundamental Keyword Liver Segmentation and Liver Cancer Detection Primary Keywords using (AND) Liver AND segmentation AND machine AND learning AND deep AND learning Secondary Keywords using (OR) Liver OR Cancer Thus the query for searching the documents in Scopus is: (TITLE-ABS-KEY (liver AND cancer) OR TITLE-ABS- KEY (lever AND segmentation) AND TITLE-ABS- KEY (machine AND learning) OR TITLE-ABS- KEY (deep AND learning)) AND (LIMIT-TO(PUBYEAR , 2021) OR LIMIT- TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT- TO (PUBYEAR , 2018) ORLIMIT-TO (PUBYEAR , 2017) OR LIMIT- TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR ,2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT- TO (PUBYEAR , 2012).

PERFORMANCE ANALYSIS:

VOSviewer 1.6.5 is the software that is used for the database analysis in addition to the analysis form Scopus.It provides a very effective way to analyze the co-citations, co- occurrences, bliometric couplings etc. (Deshpande et.al.2020) Two types of analysis are performed - Statistical Analysis of Databases that includes documents by source, year, subject area, type, country, author, affiliation, and top funding agencies. Second type of analysis is the Network Analysis of Databases. It has different relationships such as Co-authorship, Co-occurrence, Citation Analysis, andBibliographic coupling. III. RESULTS AND DISCUSSION Analysis is performed by two different ways, statistical analysis ofdatabase and network analysis. 3.1 Statistical Analysis 4.1.1 Document Analysis by Sources Database indicates differentsources including conferences, journals, book chapters, notes, letters, reviews, and so on. Year-wise publication statistics are shown in the table. Figure shows the graphical representation of the sources with number of documents.

CONCLUSION:

Liver cancer and liver segmentation Bibliometric survey is carried out by using the most popular and the largestdatabase that is used worldwide- Scopus. The documents for the analysis are considered between the years 2012 to 2020. By the keywords search with AND and OR operators a total of 518 articles were obtained. The analysis is done byconsidering different parameters. This is followed by China with 07 documents. “Human” is the keyword having maximum documents. Maximum documents are published in the year 2020. The subject area Computer Science and Engineering covered almost 29 % of the documents. As far as, the type of document is considered, article of journal are at first position followed bythe conference papers. China is having the highest documents, as far as the country analysis is concerned. India VOSViewer 1.6.5 version is used for the network analysis. The different analysis types such asco-authorship analysis co-occurrence analysis citation analysis and bibliographic coupling are the different ways to analyze the same. Outcome of these different network analyses is an indication towards the significant information about work mentioned above. It could also be concluded that the major work in liver cancer and liver detection is done in 2020. In the upcoming years a very vast and major work is expected in this area.

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