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# Liver Segmentation and Liver Cancer Detection Based on Deep Convolutional Neural Network: A Brief Bibliometric Survey

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## ABSTRACT

**Background:** 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 of the databases with different categories such as documents by source, year, and county and so on. Analysis is also done by using different units of analysis such as co-authorship, co-occurrences, citation analysis etc. For this analysis Vosviewer Version 1.6.15 is used.

**Results:** In the study, a total of 518 articles on liver segmentation and liver cancer were obtained between the years 2012 to 2020. From the statistical analysis and network analysis it can be concluded that, the maximum articles are published in the year 2020 with China is the highest contributor followed by United States and India.

**Conclusions:** Outcome from Scoups database is 518 articles with English language has the largest number of articles. Statistical analysis is done in terms of different parameters such as Authors, documents, country, affiliation etc. The analysis clearly indicates the potential of the topic. Network analysis of different parameters is also performed. This also indicate that there is a lot of scope for further research in terms of advanced algorithms of computer vision, deep learning and machine learning.

**Keywords:** liver segmentation, liver cancer, machine learning, deep learning, citation, co-occurrence

## I. INTRODUCTION

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 cancer and intra-hepatic bile duct cancer in USA alone in 2020 (ACS, 2020).

Liver is largest gland and important metabolic organ of 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 instigates in the tissue of the liver. 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 of liver cancer**.** A liver Hemangioma is made up of a tangle of blood vessels (Bosch et al., 2004).

Secondary metastatic liver cancer 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 tumors is required in the disease diagnosis. However due to the intensity of homogeneity inside liver , shape of liver, low contrast, 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, 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. The performance of the classifier is sensitive the features extracted using feature extraction algorithm. These systems are prone to the noise, illumination changes, occlusion, lower contrast and blur in the images.

Of late, the deep convolutional neural network (DCNN) has been presented for many image processing applications that can give superior performance compared to the hand crafted raw features which are low level features. It has achieved popularity for the image segmentation, recognition and classification (Zhang et al.,2017, Simonyan, 2014). However, because of unavailability of larger public database very little work is carried out for the liver cancer detection using deep learning algorithms.

Now a day, some of researchers have worked on deep learning based approaches for the liver segmentation and cancer detection. A DCNN consists of three channels that corresponds to the three ART, DL and NC models and applied for focal liver lesion (FLL) detection. They have used contrast enhanced CT images (Yasaka et al., 2017). Further, combination of a DCNN with a recurrent neural network (RNN) has been presented for the extraction of spatial and temporal parameters for FLLs detection in CT images (Liang et al., 2018). Fine tuning of DCNN helped to improve the FLLs classification performance (Wang et al., 2018)

In this work, we propose early detection of the liver cancer based on DCNN. DCNN is used for the salient feature extraction that has high level representation of spatial and temporal capability, highly correlated features, more discriminancy between raw features and more internal dependency of the raw features. In this, we propose categorization of three types of liver cancer such as Hepatocellular carcinoma (HCC), Hemangioma and Metastatic liver cancer. The proposed system includes of liver segmentation, liver feature extraction and classification.

Various works is carried out for the lever segmentation, liver tumor and cancer detection using machine learning methods and deep learning (DL) approaches. This section provides the highlights of the recent work employed for the liver segmentation and cancer detection.

## 1.1 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, various methods 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 cut method (Guodong et al., 2015), 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. Unsupervised Deep Adversarial Networks (DAN) along with Weighted Loss Function (WLF) presented the semantic liver segmentation on abdominal CT images (Kaijian et al., 2019). Further, the convolutional neural network (CNN) has been utilized for the segmentation of lesion in liver CT images that has given a dice similarity coefficient of 80.06% (Wang et al., 2013). It is observed that combination of a DL algorithm along with graph cut refinement increases the efficiency of segmentation of the liver CT images (Lu *et al.*, 2017).

In the graph-cut technique, the liver part is roughly considered as the foreground and peri-hepatic structure is considered as the background part. Then using cut methods the foreground and backgrounds pixels are separated in the homogeneous regions (Boykov et al, 2001).

Intensity-based techniques consider the gray intensity value of the pixel with the neighborhood pixel intensity to decide the texture of the liver. In the techniques, the seed points are manually place by the expert in the liver parenchyma. The pixels that matches with the seed pixels are clustered collectively to form the homogeneous texture region. This system was semi-automatic method and performance was dependent on the manual seed points (Lopez et al., 2013). Because of the unavailability of the shape control facility, intensity based methods often resulted in leakage in the manual seeded area, rough ridges and edges. It has found that intensity based techniques are not suitable for the MR images having highly heterogeneous texture (Sharma and Agrawal, 2010).

Machine learning based methods such as support vector machines (SVMs) (Defeng et al., 2012) and random forests (Norajitra et a., 2015) has been successfully presented for the quantitative feature extraction of the image texture. These algorithms have given better performance and highly discriminative capability than the intensity based methods. Sometimes, because of the noise and rotation these method can lead to the leakage or coarse segmentation. Recently, CNN has was presented for the liver segmentation to extract the quantitative features rather than hand-crafted features. It could segment heterogeneous liver texture in minimum time span (Elshaer et al., 2016).

In a recent survey report, several DL approaches such as deep DCNN (DCNN), auto encoders (AE), fully convolutional network (FCN) and deep belief networks (DBN) were presented for cancer detection and analysis (Hu *et al.*, 2018). Recently deep learning and gradient based liver segmentation done to achieve precise contours of liver and tumor inside. A novel 3D CNN has been investigated for the primary and secondary liver cancer detection using diffusion weighted MRI (DW-MRI). It has shown significant improvement (83%) in the liver detection rate (Eleftherios et al., 2019). They addressed imbalance issue in segmentation and analyzed that re-weighting and similarity based measurement as loss function is not better method (Zhang et al., 2020). Again, to deal with the imbalance in contrast and frequency occurrences, cascade U-ResNets has been presented for the liver segmentation and lesion segmentation (Xue-feng et al., 2020).

### 1.2 Survey of Liver Cancer Detection

For the liver cancer detection various texture, shape and gradient based features have 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, 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).

Further, an edge based distance regularized level-set evaluation method has been presented to segment the tumor, calculi, cyst and normal liver. Edge based distance has shown the correlation between texture and shape of the liver (Li et al., 2010). A multi-channel fully convolutional network (MC-FCN) model has shown significant improvement in the liver tumor detection. Convolutional network comes under the shallow learning algorithm which helped to increase the local representation of the raw features and described the ensemble texture properties (Sun et al., 2017). Various statistical techniques such as gray level co-occurrence matrix (GLCM) have been used for statistical attribute extraction. GLCM features consisted of energy, entropy, correlation and homogeneity. Gray level intensity is very common feature for the depiction of the liver CT images which are capable of representing the edges, boundries and the fine changes over the texture of liver CT images. It is simple to implement, stable and robust for low database systems. The GLCM based systems has limited performance due to need of user interaction, blur, noise, uneven intensity distribution and contrast of the CT images. in case of smaller foreground or background performance of the system is degraded (Hu et al., 2018).

Learning based algorithms are better suitable for the liver cancer detection. When the performance of back propagation neural network (BPNN) and SVM for liver tumor detection compared it is found that BPNN gives superior result (73.23% accuracy) compared to SVM. Though, in case of accuracy BPNN has given better performance than the SVM, time required for the training and the testing is more for BPNN. BPNN needs more parameter tuning compared to SVM (Devi et al, 2015). (Rajagopal et al., 2014) Proper tuning of Support vector machine resulted in accuracy of 97.83% for liver tumor detection in CT images. To deal with under segmentation problem an automatic fuzzy clustering scheme along with a multi-SVM classifier has been presented to classify liver diseases such as hem, Cyst and HCC (Sakr et al., 2014). From the survey of the traditional machine learning based techniques it is observed that the performance of the liver cancer detection system highly dependent on the raw features extracted using feature extraction algorithms. Raw features are having less correlation and uniqueness in the local representation of features.

Earlier Deep learning algorithms were popular for the classification of the liver cancer using traditional features (Kaizhi *et al.*, 2014). Fully CNN (FCNN) is simple to implement and gives better scarcity. It has shown better performance for the lower database with the help of 3D segmentation of liver (Ben-Cohen *et al, 2016).* The Hybrid Feature Selection approach (HFS) founded on neural network was successfully applied for liver cancer detection (Kim and Park, 2018). Subsequently, Multi-scale candidate generation (MCG) with the help of super-pixel segmentation has been presented for the liver tumor segmentation method that utilized an active contour model (ACM) and 3D fractal residual network (ResNet). It enhances the sensitivity of the deep network to detect liver tumor and minimizes computation complexities occurred due to redundant data (Bai et al., 2019). Further, to detect the liver lesion, combination of Watershed Transform (WT) and Gaussian mixture model (WT-GMM) based on deep learning has been used. It resulted in 99.38 % recognition rate (Das et al., 2019).

Because of variety of liver cancers and liver images, various traditional and machine learning based techniques has been presented for computerized automated liver tumor detection (Duda et al., 2013). The contribution of the bio-inspired computational methods and natural computing methods for the cancer detection in the medical images are highlighted in (Mitra and Shankar, 2015). Recently, CCN presented for image analysis and recognition that has higher representation, dimensionality reduction (Ker et al., 2017). Recently, for the enhancement of the edge information of the CT images multi-scale image fusion and non-sub- sampled contourlet transform has been employed that resulted in contrast enhancement of the real time CT images (Lakshmi et al., 2020).

Automatic segmentation of liver lesion is tough task because of many factors such as liver stretch, small ferocity divergence between lesions and nearby tissue. Deep learning architecture based on Probabilistic neural network have inculcate in better performance for liver lesion detection in extreme challenging conditions (Sureshkumar et al., 2020). Further, for the benign and malignant HCC liver cancer detection, deep inception net has been explored which resulted in 96 % accuracy. The inception network was used to predict ten frequent prognostic genes in HCC. It has shown that CNN can help in the gene mutation classification and detection in liver cancer (Chen M., 2020). Afterward, effect of deep learning has been presented to assist pathologists to distinguish between hepatocellular carcinoma and cholangio-carcinoma, eosin-stained whole-slide images (WSI) and hemato-xylin. Traditional machine learning algorithms have high computational cost and redundant features. Recent deep learning models dealing with these problems are facing challenges in network topology and network hyper-parameter optimization. Therefore, a hybrid algorithm composed of LeNet-5 model and ABC algorithm (LeNet-5/ABC) proposed for liver lesions detection (Ghoniem R., 2020). Later, a deep learning model consisting of three UNet has been presented for the liver segmentation and cancer detection. They have used one UNet for the liver segmentation, second UNet for the tumor segmentation from segmented liver and third UNet for the tumor segmentation from the complete abdominal images (Ayalew et al., 2020)

## II. MATERIALS AND METHODS

### 2.1 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

**Table 1: List of Primary and Secondary 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 ) OR LIMIT-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 ) )

## 2.2 Initial Search Outcomes

On the Scopus database, different keywords are used for the searching related to our work. Different publications are obtained. Language is one of the parameter for analysis. It is found that, English language has the most of the publications of 508, followed by Chinese.

**Table 2: Language Trends of Publications**

| Language of publishing | Publication count |
|---|---|
| English | 508 |
| Chinese | 7 |
| German | 1 |
| Persian | 1 |
| Spanish | 1 |
| Total | 518 |

**Source: http://www.scopus.com (assessed on 2nd Dec. 2020)**

## 2.3 Publication outcome based on Top 15 Keywords

During the search, many keywords are found in addition to the fundamental keywords. Following table shows the top 15 keywords. Human is the keyword having the most of the publications. Machine learning keyword also contributed comparable with the highest keyword.

**Table 3: Publication Analysis based on Top 15 keyword Analysis**

| Sr. No. | Keyword | Publications |
|---|---|---|
| 1. | Human | 301 |
| 2. | Machine Learning | 272 |

| | | |
|---|---|---|
| 3. | Article | 255 |
| 4. | Humans | 172 |
| 5. | Deep learning | 149 |
| 6. | Priority Journal | 144 |
| 7. | Liver Cell Carcinoma | 129 |
| 8. | Male | 125 |
| 9. | Female | 115 |
| 10. | Diseases | 114 |
| 11. | Major Clinical Study | 112 |
| 12. | Controlled Study | 99 |
| 13. | Liver Cancer | 93 |
| 14. | Procedures | 91 |
| 15. | Adult | 87 |

**Source: http://www.scopus.com (assessed on 2nd Dec. 202**

## II. 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, and Bibliographic coupling.

## III. RESULTS AND DISCUSSION

Analysis is performed by two different ways, statistical analysis of database and network analysis.

### 3.1 Statistical Analysis

#### 4.1.1 Document Analysis by Sources

Database indicates different sources 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.

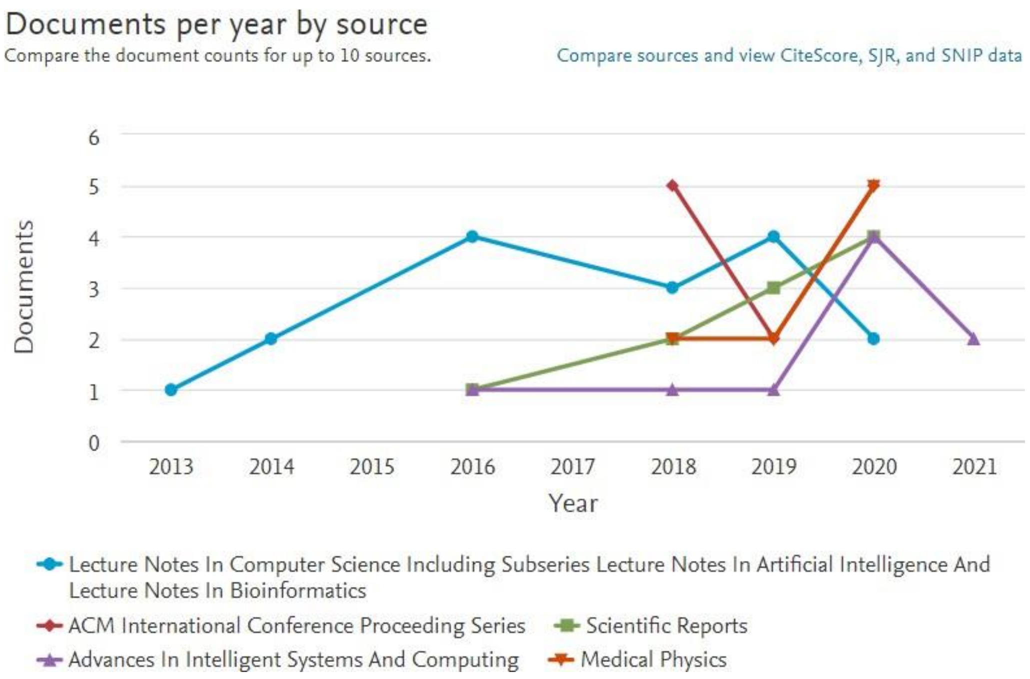


**Figure 2: Analysis of Documents by Sources**

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

### 1.1.2 Documents Analysis by year

Documents are collected from the year 2012 to 2020 including different sources such as conferences, journal, book chapter etc. The table shows the statistics and graph is as shown in figure. The highest publications are in the year of 2020 followed by 2019.

**Table 4: Number of Publication by Year**

| Year | Number of Publications |
|---|---|
| 2021 | 5 |
| 2020 | 209 |
| 2019 | 121 |
| 2018 | 55 |
| 2017 | 43 |
| 2016 | 27 |
| 2015 | 19 |
| 2014 | 23 |
| 2013 | 12 |
| 2012 | 4 |
| **Total** | **518** |

**Source: http://www.scopus.com (assessed on 2nd Dec. 2020)**

### 4.1.3 Documents by Subject Area

Liver cancer is purely the medical term. Hence maximum documents are found under medical category (27%). Following to the medical category, computer science (18.5%) and engineering (10.6%) which combinedly covers 29.1% of documents.

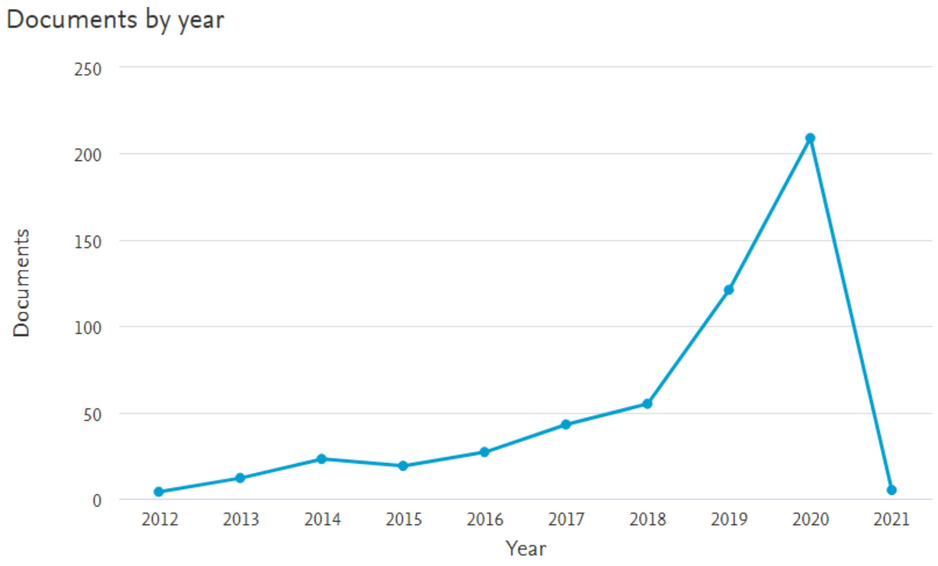


**Figure 3: Analysis of Documents by Sources**

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

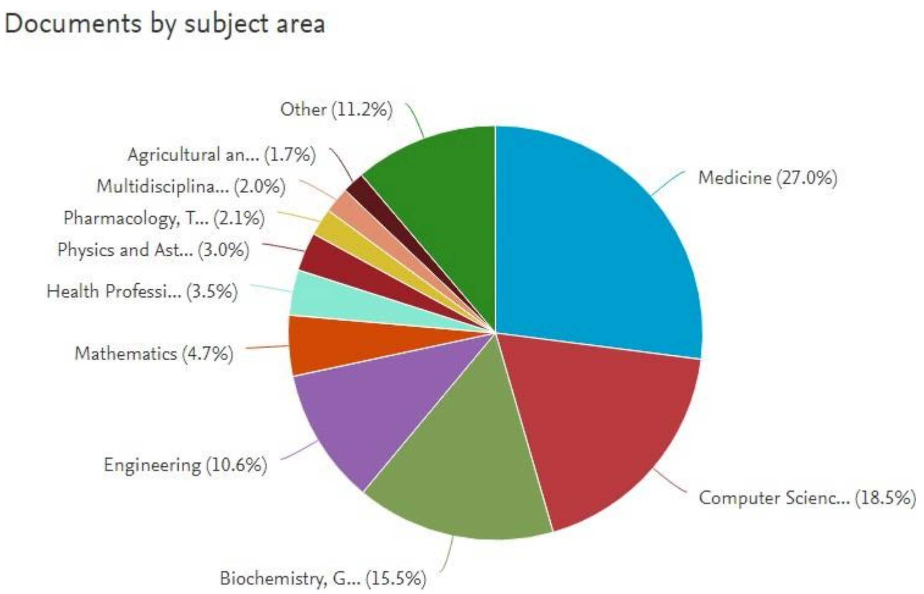


**Figure 4: Analysis of Documents by Subject Area**

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

### 4.1.4. Documents by Type

It is seen form the analysis that, most of the publications are journal articles followed by conference papers.

**Table 5: Analysis by Document Types**

| **Sr. No.** | Document type | Publications |
|---|---|---|
| 1. | Article | 332 |
| 2. | Conference Paper | 93 |
| 3. | Conference Review | 16 |
| 4. | Review | 45 |
| 5. | Book Chapter | 11 |
| 6. | Short Survey | 1 |
| 7. | Editorial | 13 |
| 8. | Letter | 2 |
| 9. | Note | 5 |
| **Total** | | **518** |

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

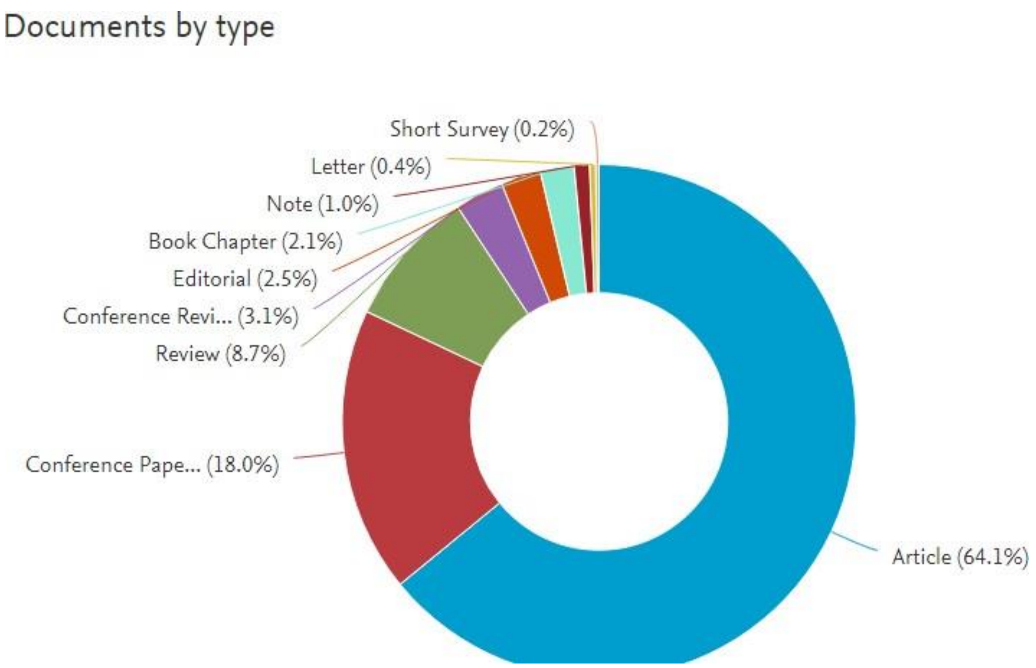


**Figure 5: Analysis of Publications by Document Type**

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

### 4.1.5 Analysis of Publications by Country or Territory

Scopus database is analyzed for territory or countries by with the number of documents. It shows that China is the highest contributor followed by United States and then India stands at third position.

### 4.1.6 Documents by Author

In this analysis, authors with the number of publications are considered. Top 10 authors with this comparison is shown in the figure. It is found that Kadaury S. has the highest number of publications of 8 in the area. Maximum authors have 4 to 6 publications as an average.

### 4.1.7 Documents by Affiliations

In this analysis, top 10 affiliations are considered. It is found that, Chinese Academy of Sciences has the highest document followed by Ministry of Education, China.

### 4.1.8 Analysis by Funding Sponsors

National Nature Science Foundation, China spent the highest funding. Education and health sector also contributed some of the sponsorship.

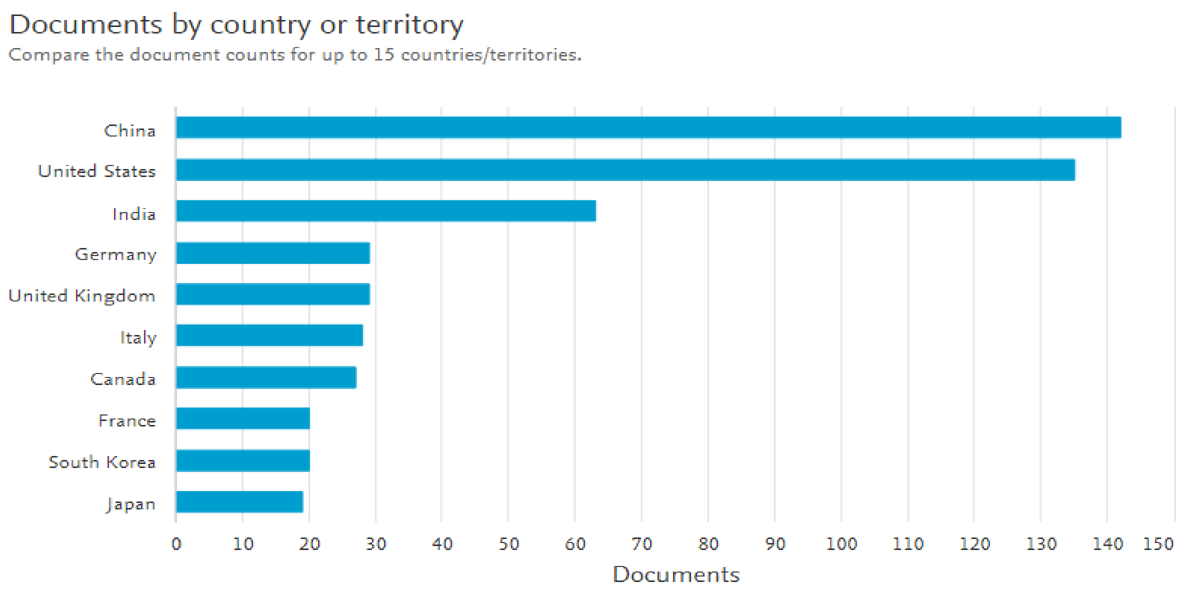


**Figure 6: Analysis by Country**

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

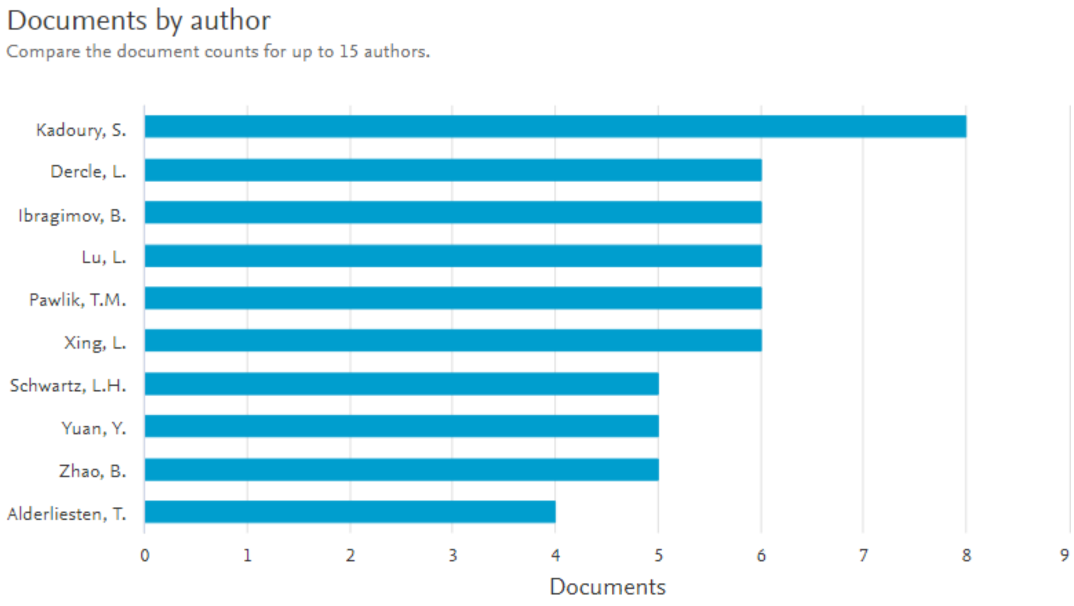


**Figure 7: Analysis of Documents by Author**
**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

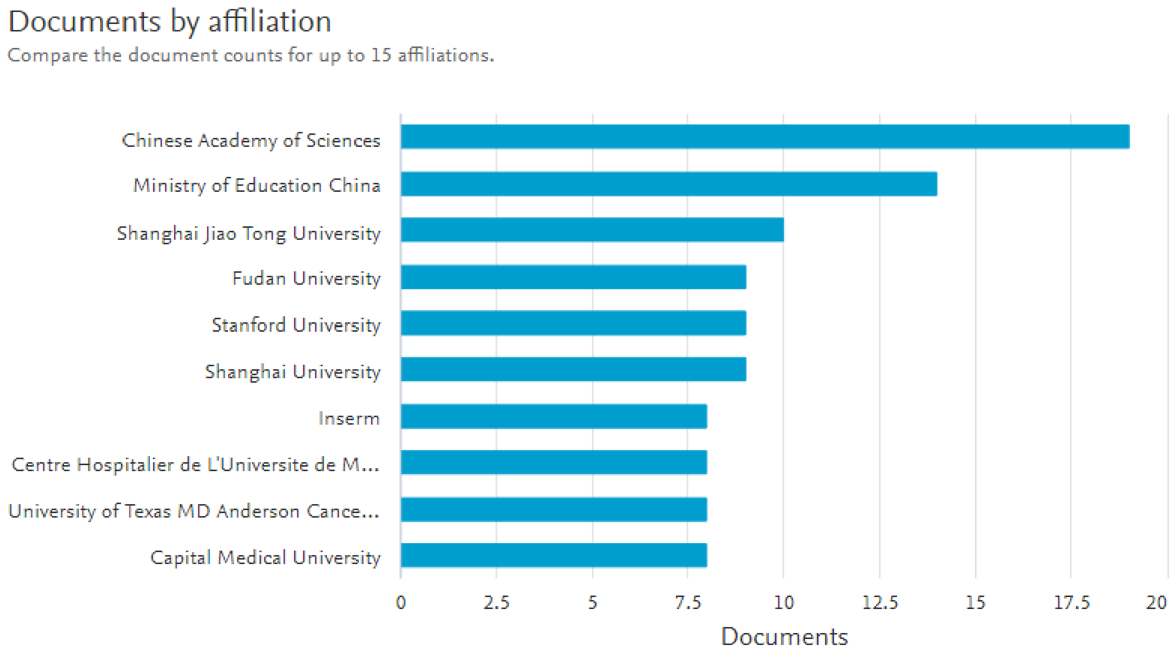


**Figure 8: Analysis of Documents by Affiliation**

**Source: http://www.scopus .com (assessed on 2nd Dec. 2020)**

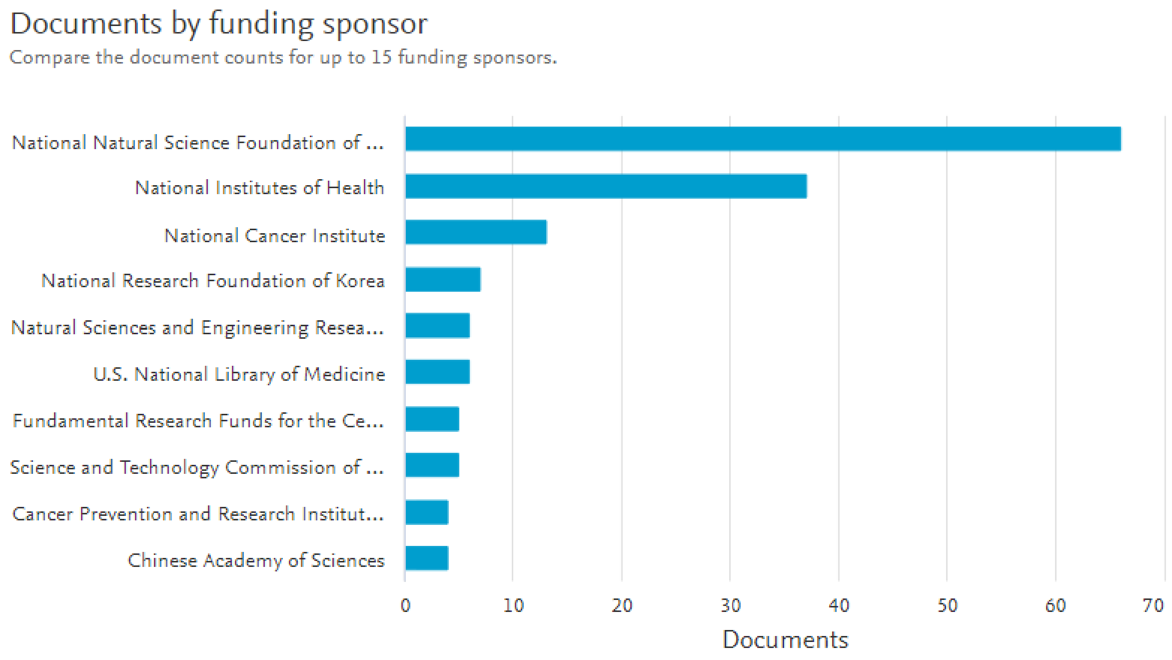


**Figure 9: Analysis of Documents by Funding Sponsor**

**Source: http://www.scopus .com (assessed on 2$^{nd}$ Dec. 2020)**

## 4.2 Network Analysis

### 4.2.1 Co-authorship Analysis

#### A) Co-authorship in terms of Authors

This analysis is considered in terms of authors, organizations, and countries.

If a document has a very large number of authors (25 authors in this case), the document is ignored from the analysis. An author with minimum of 2 documents is considered as a threshold value in this case.

It is observed that, within the total of 2368 authors, only 347 authors met this threshold criteria. Zhang Y. has the highest number of documents equal to 10 in this analysis. Also Li X. has got the maximum citations those are equal to 297. So these are only shown in the figure.

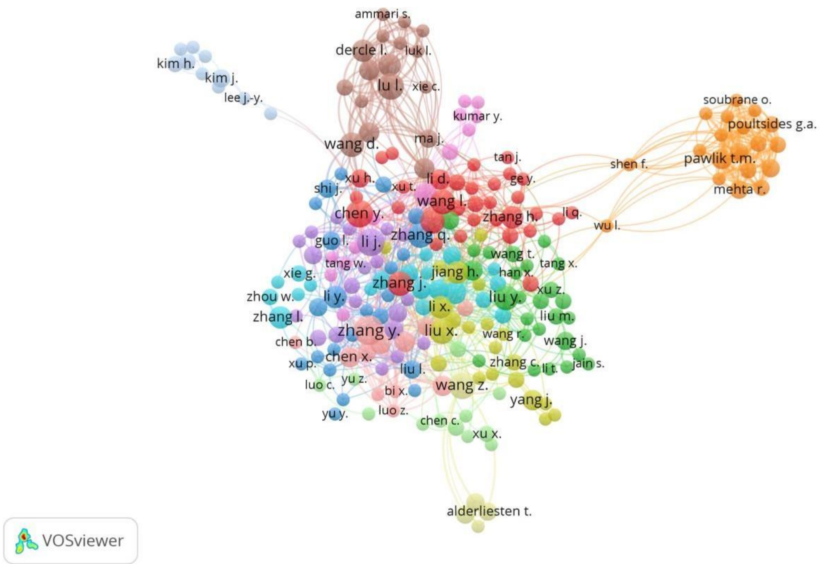


**Figure 10: Co-authorship Network Analysis in Terms of Authors**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

## B) CO-authorship in terms of Organizations

Considering the minimum number of citations in an organization as 4 and minimum number of 2 documents per organization, Co-authorship is calculated in terms of organizations.

There are a total of 1717 organizations, out of which 30 meet the threshold criteria. The same is explored in the figure. Two organizations are having the highest link strength of 9. These organizations are Department of surgery , Department of surgery…….. Department of radiology….has the highest number of citations of 68. A total of 9 organizations have highest link strength of 4 with the highest citations of 47 by center for biomedical informatics, Harvard medical school, Boston, United States (with 2 documents).

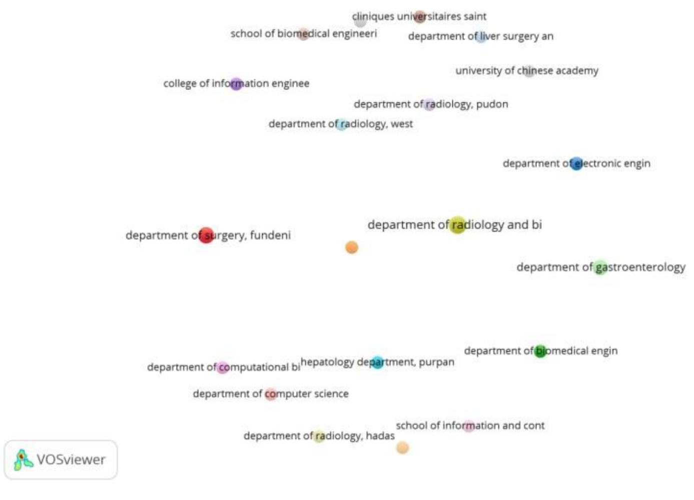


**Figure 11: Co-authorship analysis in terms of Organizations**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

### C) Co-authorship in terms of Country

A total of 79 countries found to have databases related to this field. With the threshold of 5 documents per country, a total of 32 countries found to have the articles.

China found to have highest number of documents with 142 documents and United States found to have the highest number of citations of 17has 63 number of documents and 323 citations.

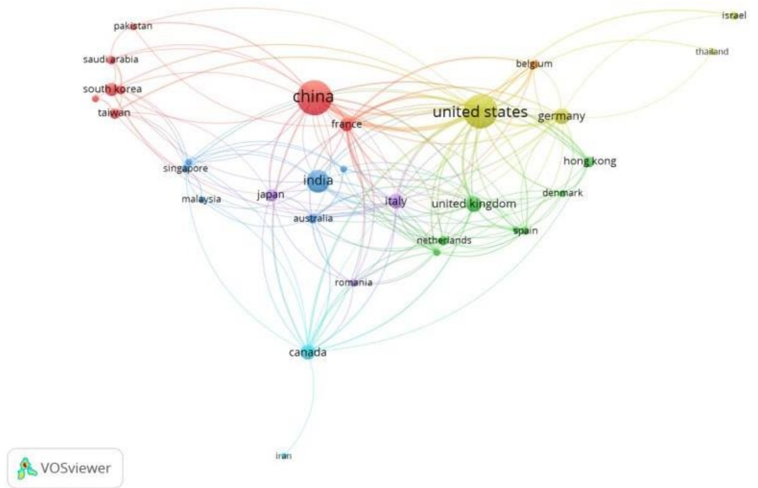


**Figure 12: Co-authorship analysis in terms of Countries (Scale is with number of documents)**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

### 4.2.2. Network Analysis of Co-occurrences

### A) Co-occurrence analysis in terms of all keywords

Keywords are the most important features of any article. Co-occurrences of different keywords are analyzed. 5 is the threshold considered here. It is found that 560 keywords met the threshold out of 5554 in total.

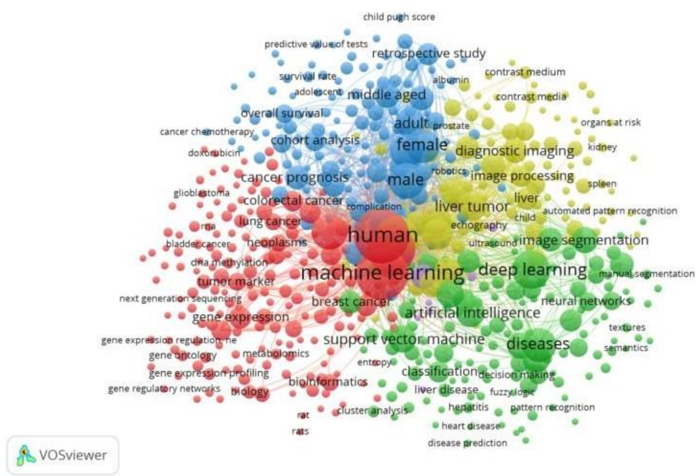


**Figure 13: Co-occurrence Analysis in Terms of All Keywords**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

### B) Co-occurrence analysis in terms of Author keywords

For this co-occurrence the minimum threshold is considered to be of 5 per author. Out of 1256 keywords, threshold is crossed by 44 keywords.

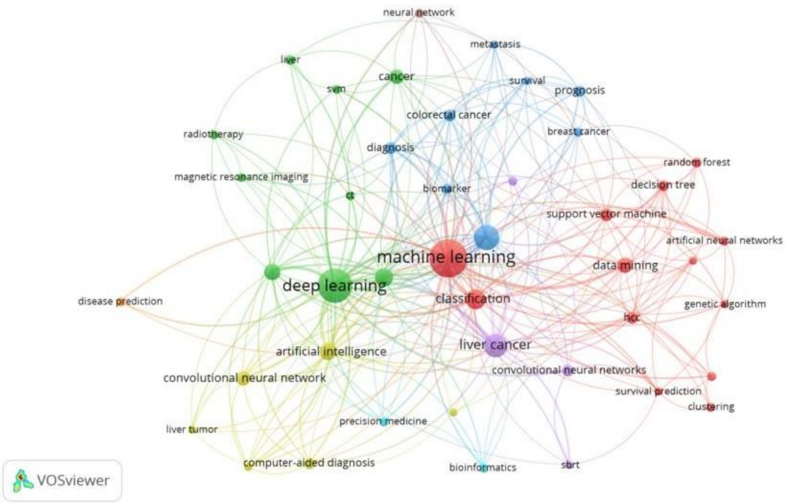


**Figure 14: Co-occurrence Network Analysis (Author Keywords)**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

### C) Co-occurrence in terms of Index Keywords

Index keywords are 4782 in total. Co-concurrence in terms of these words outcomes 533 keywords that met the threshold.

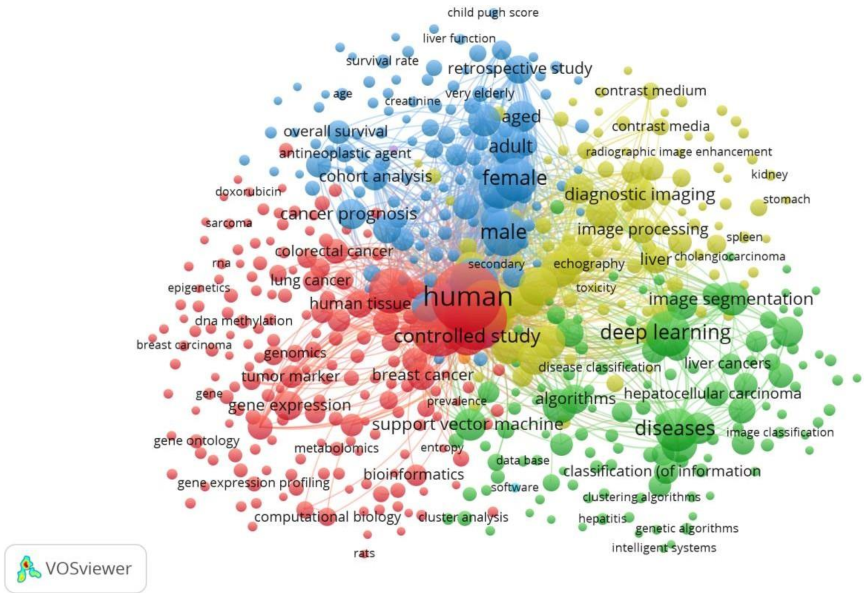


**Figure 15: Co-occurrence of Index Keywords**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

### 4.2.3. Network Analysis of Citations

Citations could be analyzed in the units of sources, documents, authors, country, and organization.

#### A) Citation Analysis of Documents

There are a total of 518 documents, with a minimum of 5 citations considered per document. It is found from the analysis that, 169 documents met the threshold. The comparable names of authors with higher citations are li. X(2018), Sun R (2018), and Chaudhary K. (2018).

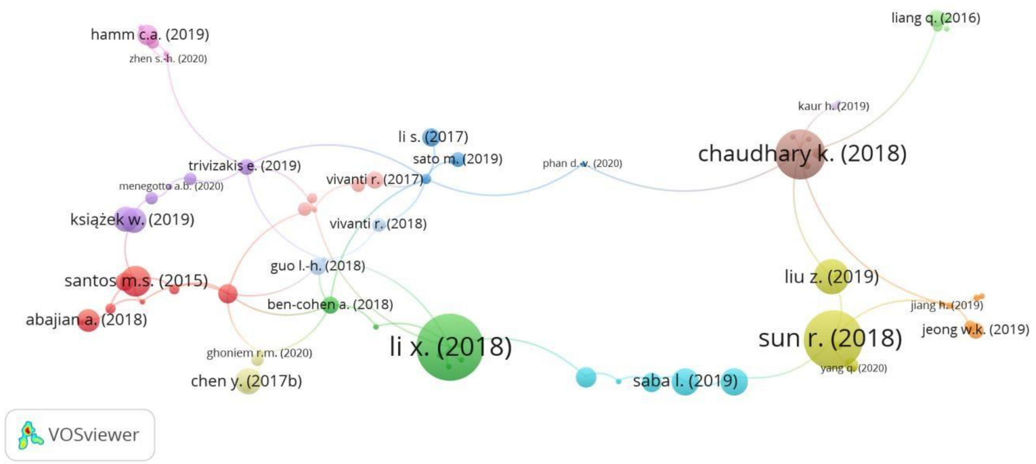


**Figure 16: Network Analysis of Citations (In terms of Documents)**

**Source www.scopus.com, accessed on 2nd Dec. 2020**

#### B) Citation Analysis of Sources

Sources can be considered as one of the analysis parameter here. This database search shows a total of 285 sources. By considering a minimum of 5 documents per source, 22 met the threshold. Analysis also indicates that, Journal of biomedical informatics has got maximum number of citation of 235.

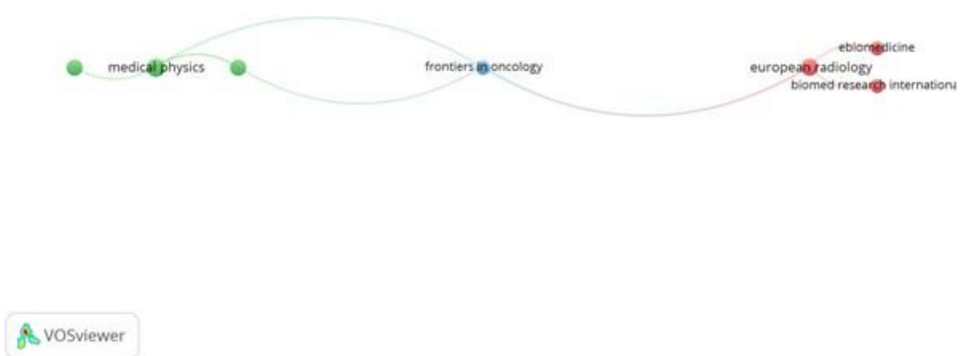


**Figure 17: Network Analysis of citation by sources, Source www.scopus.com, accessed on 2nd Dec. 2020**

### C) Citation analysis by Authors

In this analysis the threshold considered here is 3 citations per author. Amongst a total authors of 2368, 118 authors reached the threshold value. Wang x. has maximum citations of 243.

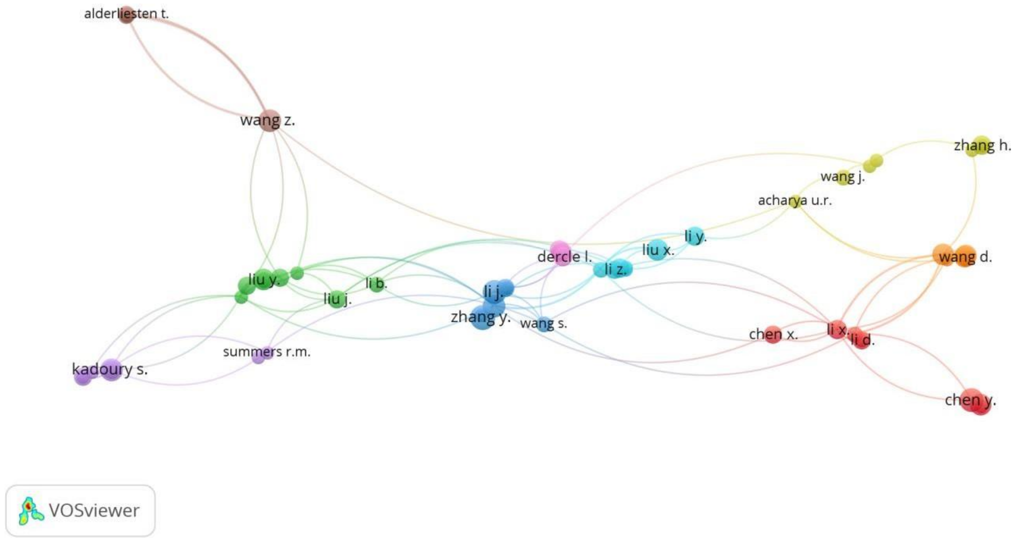


**Figure 18: citation analysis by Authors, Source www.scopus.com, accessed on 2nd Dec 2020**

### D) Citation analysis by organization

There are total of 1717 organizations linked with this database. Threshold value considered in this analysis is 2 citations per organization and 2 documents per organization. A total of 33 organizations met the threshold. Maximum citations are with the Department of radiology and bioinformatics yale school of Medicine. It has 68 citations.

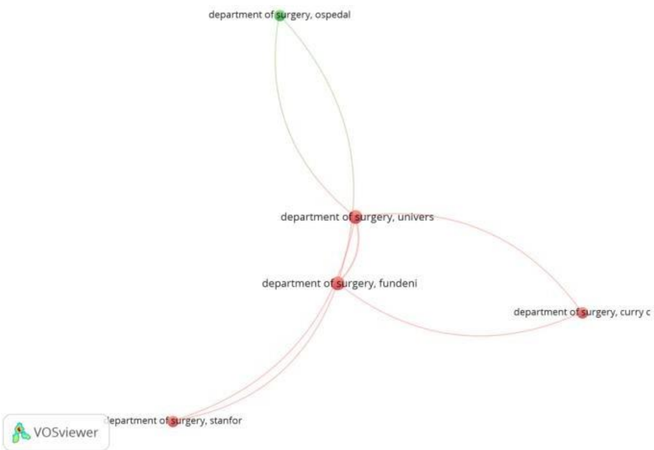


**Figure 19: Citations by Organizations, Source www.scopus.com, accessed on 2nd Dec 2020**

**E) Citation analysis by country**

Out of a total of 79 countries having the database of the current search, 32 met the threshold criteria. Analysis has a threshold of minimum of 5 documents.

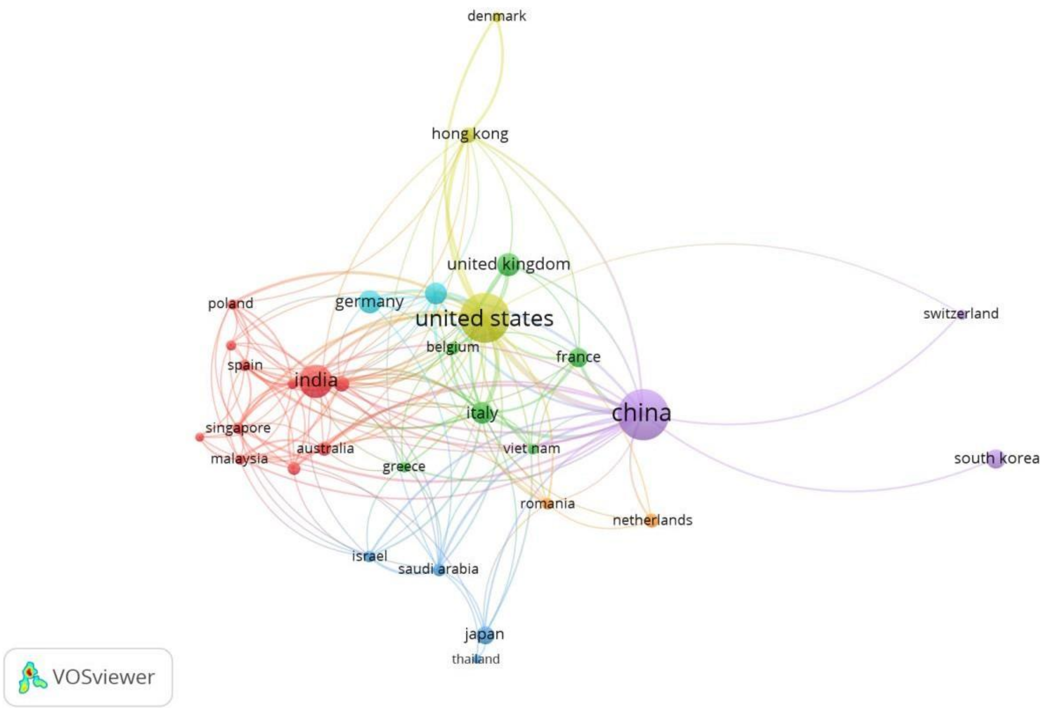


**Figure 20: Citation analysis of country, Source www.scopus.com, accessed on 2nd Dec 2020**

### 4.2.4. Network Analysis of Bibliographic Coupling

**A) Bibliographic Coupling of Documents**

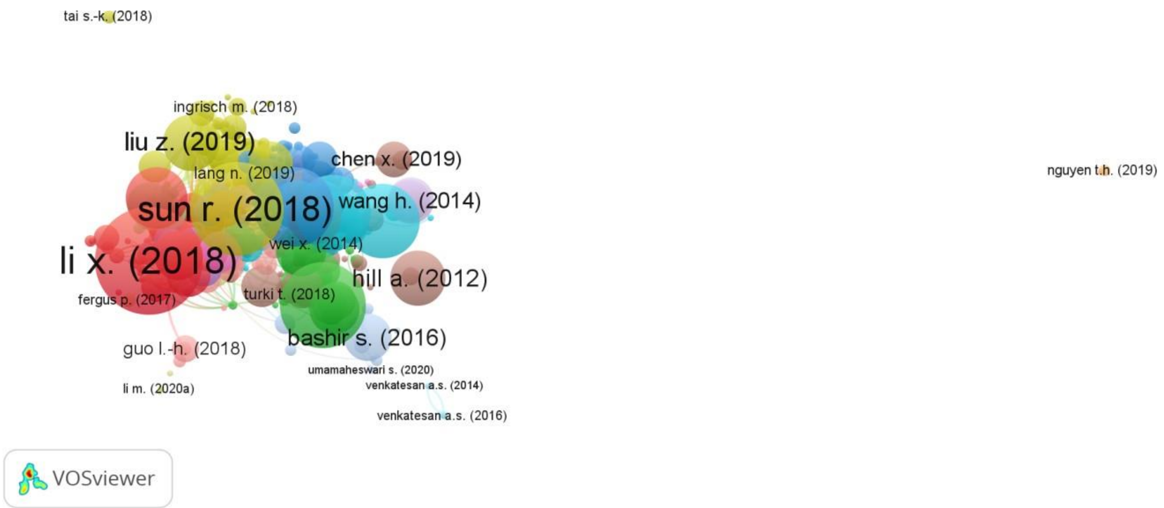


**Figure 21: Bibliographic coupling of documents, Source www.scopus.com, accessed on 2nd Dec 2020**

**B) Bibliographic coupling of Sources**

In this analysis, 22 sources met the threshold amongst a total of 285 sources. Threshold considered here is 5 documents per source.

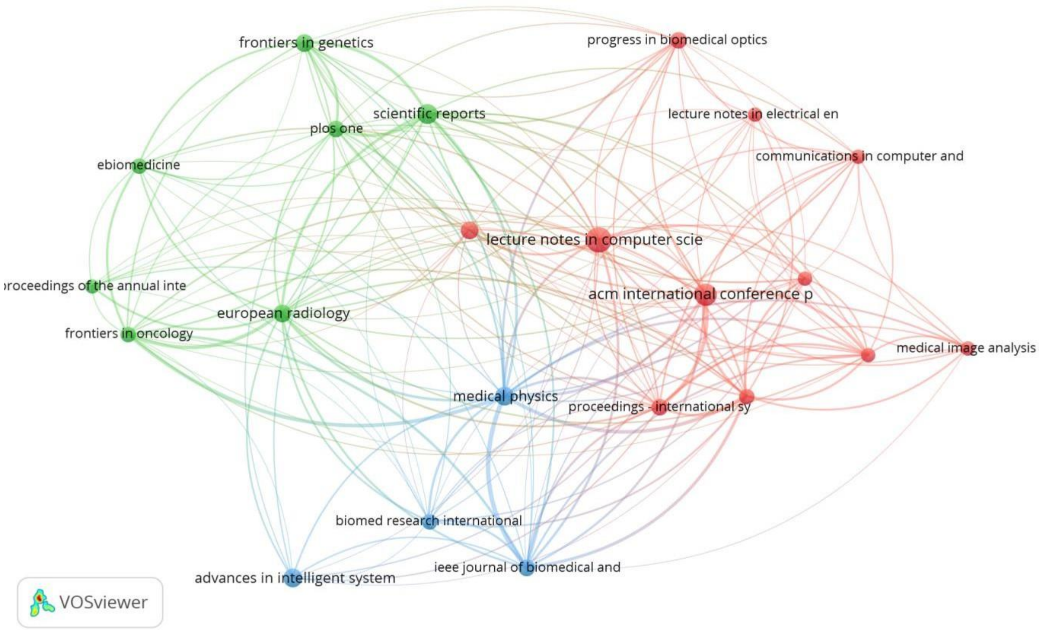


**Figure 22: Bibliographic coupling of Sources, Source www.scopus.com, accessed on 2nd Dec 2020**

## IV. CONCLUSION

Liver cancer and liver segmentation Bibliometric survey is carried out by using the most popular and the largest database 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 by considering different parameters. It is observed that English language contributed the most in the database with a total of 508 articles. 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 by the conference papers. China is having the highest documents, as far as the country analysis is concerned. This is followed by United States and India

VOSViewer 1.6.5 version is used for the network analysis. The different analysis types such as co-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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