The Application of Convolutional Neural Networks to Improve the Efficiency of Lung Cancer Detection

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Abstract

The effectiveness of various methods of lung cancer diagnosis was analyzed and used in order to compare the effectiveness of convolutional neural networks (CNN) combined with computed tomography (CT) to evaluate whether convolutional neural networks should be implemented in the near future. Papers included in this systematic review recorded metrics of speed, false positive rate, and sensitivity of lung cancer diagnosis. Findings suggest that the method of using convolutional neural networks with computed tomography scans may be more effective than current methods of a lung cancer diagnosis.

Keywords: convolutional neural networks, computed tomography scans, artificial intelligence, lung cancer

Introduction

Lung cancer is one of the most prevalent causes of cancer-related death all over the world, and it is the most common cause of cancer death in the United States (World Health Organization, 2017). There are many different causes of lung cancer, notably smoking and radon exposure. The primary cause of lung cancer is smoking, which, specifically in the United States, there are an estimated 37.8 million people smoke, with more than 16 million Americans living with a smoking-related disease, such as lung cancer (Center for Disease Control and Prevention, 2016). Smoking is particularly deadly because it can cause denaturation of cells in the lung, which can affect the ways people are able to take in oxygen and breathe. As well as that, it is especially important to get lung cancer detected as fast as possible, as the survival rate for people who do get on lung cancer treatment immediately after the cancerous growth being discovered is about 45%. The survival rate only goes down from there, going down to as little as a 2% survival rate when the cancer is discovered in its late stages. In addition, the signs of early cancer growth can be minuscule and often go unnoticed, leading to people getting treatment later into the cancer growth than necessary to have a higher rate of survival. The difficult to spot symptoms, such as posing as a normal cough, in combination with the incredibly deadly effects of lung cancer and a large smoking population have contributed to lung cancer is the highest cause of cancer death in the world (National Institute of Health, 2017).

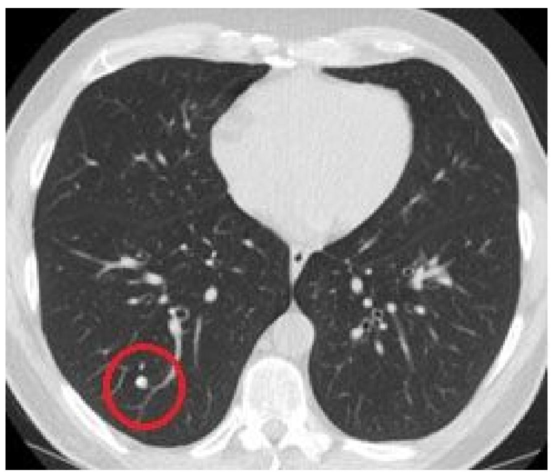

Fig. 1. The use of a CT scan to detect a lung nodule that may cause lung cancer.

Due to the frequency at which methods of lung cancer diagnosis are used, there is a necessity for methods of lung cancer detection to accurately and as fast as possible. Because of the need to detect malignant growth as fast as possible, as to not lead the cancer spread and not affect more cells causing a larger impact, many different ways of detecting lung cancer arose. Some of the methods most commonly used to detect lung cancer are chest X-rays, computed tomography (CT) scans, sputum cytology, PET scans, MRI, and tissue samples. The most common method of detecting lung cancer is the chest X-ray because it combines relatively high accuracy with a high speed to get patients results as fast as possible. With chest X-rays, a doctor uses an X-ray machine to take a 2-dimensional X-ray diagram of the lung, which can then be analyzed by a radiologist to find any malignant growth. Because of the speed of chest X-rays, they have often been favored over other methods of lung cancer diagnosis, such as CT scans and PET scans, even though many other methods of cancer detection are far more accurate. While CT scans on their own, are only a niche method of detecting lung cancer, only used in times where accuracy is a more important factor than speed, because of the unique scans they produce, CT scans can be paired with forms of artificial intelligence, in order to increase the speed that makes CT scans an overall not practical method of detecting lung cancer. A CT scan will create a 3-dimensional image of a lung, that can depict lung cell growth and possible malignant cell growth very accurately, due to its 3-dimensional nature. However, the speed at which it takes to perform the CT scan, as well as the time it takes for a human to perform the analysis of the scan, in order to spot any cancer growth and give the diagnosis. Even so, as previously stated, its 3-dimensional properties can allow it to be paired with forms of artificial intelligence that can compensate for the poor overall speed of detection.

Multiple different forms of artificial intelligence can theoretically be used in combination with CT scans, but the most feasible form is convolutional neural networks (CNN). CNNs are a unique form of artificial intelligence that is made up in layers similar to the human brain. Furthermore, CNN uses its different layers to analyze images, breaking them down into smaller images, and cross-referencing those images with online databases. This can be used in the case of detecting lung cancer, by observing CT scan and taking the many different parts of the scan, breaking them up, and using online databases to spot signs of malignant cancer growth. A CNN will make up its knowledge of lung cancer, using databases that are comprised of images in this scenario, images of malignant cell growth and tumors that are key signs of lung cancer. There are many different databases that can be used to detect lung cancer, but one of the large databases that were used in combination with CNN was the LUNA15 database. The LUNA15 is an online database of signs of malignant lung cancer growth that the majority of studies that rely on when using CNN because the CNN can utilize the very large database in order to formulate the most accurate lung cancer detections. Using large databases such as LUNA15 allows CNN to accomplish very high accuracy rates, with very low false positive rates (Khosravan & Bagci, 2018). CT scans are particularly beneficial when paired with CNN because, unlike in other methods of detection such as X-rays that create 2D images, CT scans create 3D images. This gives more area for artificial intelligence, such as CNN which needs as much information as possible, in order to make the most accurate predictions. By creating a 3D image for the CNN to survey, this reduces the room for false positives as much as possible, making CT scans the most ideal method for examining lung cancer.

False positives show the number of times that the diagnosis detects lung cancer, but the detection is incorrect, hence the name false positive. It is particularly important to reduce the number of false positives because giving people who do not need lung cancer treatments would be detrimental, as it would effectively tell someone they have lung cancer. With the danger posed by lung cancer, many patients would immediately seek treatment, not only being costly for the patient but also harmful due to many of the drawbacks of lung cancer treatments.

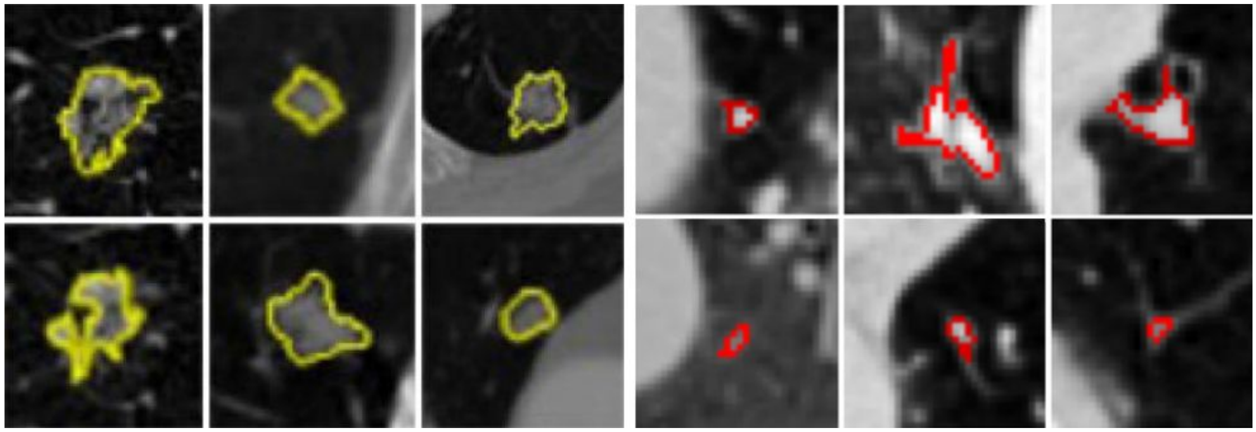

Fig. 2. CNN detecting malignant cell growth (left) vs. false positives(right)

Generally, because of the need for a qualified person to observe the tests, and a large number of tests and people that attempt to get screening results, the average wait time to get back lung cancer detection results is around two weeks. Using CNN's in combination with CT scans would make the artificial intelligence algorithm essentially compare the image found in the CT scan with other scans found in an online database to determine if the person has lung cancer. Because the neural networks can do this search quickly and can compare the image with multiple images instantaneously, as a radiologist would not be needed, this would dramatically affect the speed at which patients receive their tests back (Ding et al., 2014). In a disease like lung cancer, it is essential to get treatments far faster than this because the longer lung cancer takes to develop, the lower the rate of survival is (Athey, Suckling, & Todd, 2018). A reason for this is that lung cancer has no apparent cure, and the symptoms just need to be slowed to a point of not being relevant, which makes it necessary for patients to undergo a treatment like using CNN with CT scans. This treatment would potentially be done to increase the odds that a person could be truthfully diagnosed or determined to not have cancer, saving them money and time that it takes to scan for the lung cancer present day. It would also be beneficial to the health of the person because with lung cancer it is essential to get on treatments as soon as possible, in order to have the infected cells stay in the lung for the least time possible, and have cancer not spread (Huang & Shan, 2016). Overall, this would benefit the patient by using up less of their time and money by creating a more efficient scan that would up the diagnosis percentage of the current method.

While CNN w/ CT scans is a very appealing option because of the speed and accuracy that it can detect lung cancer at, the method lacks the credibility that comes with a doctor diagnosing lung cancer. In general, people would be more comfortable having a doctor diagnose lung cancer, rather than a form of artificial intelligence (Amato, 2013). A simple solution to this problem would be to have a doctor or scientist look over the findings of the neural network and change or support the diagnosis with their professional opinion. Although this would solve the issues associated with credibility, the pairing of a doctor with CNN could possibly compromise the speed that makes the convolutional neural network appealing in the first place. This would pose a moral dilemma that could only be solved by either people becoming more comfortable with having artificial intelligence make these large influential changes in their lives, such as diagnosing them with cancer and actually trust the results. As well as that, doctors could possibly be given special training in order to help maintain the speed of the scans, but this kind of training would not yet be available due to the modernity of CNN and their use for detecting forms of cancer.

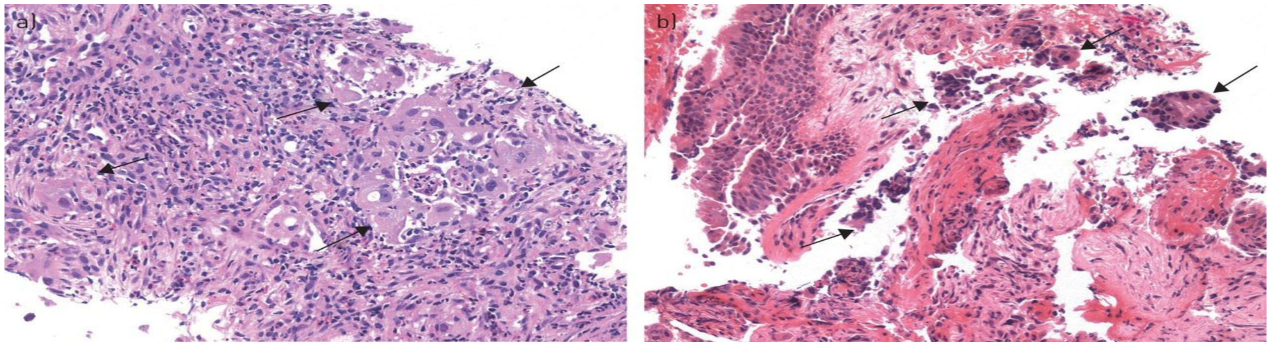

Fig. 3. On the left shows an early stage lung, beginning to show the signs of possible lung cancer. The other image (right) shows the development of lung cancer as it becomes enlarged and breaking up cells in the lung. This leads to a loss of function in an essential organ, which is part of the reason why lung cancer is so deadly, in combination with the high amount of mutations caused by smoking.

A reason why this change may be necessary is that to read CT scans and detect a large number of nodules with accuracy takes a large amount of effort from the person reading the scan to make the diagnosis. Using a computer-aided detection (CAD) would help in making the detection of nodules more cost effective and possibly more accurate in comparison (Wang, 2017). To this end, a variety of approaches have been proposed for lung nodule detection in CT images. Usually, a nodule detection system would start by generating nodule objects and classifying them based on certain features that are predetermined. This works in order to separate the harmful nodules from the rest of the cells involved in the scan. One major limitation of these features is the requirement of nodule candidate segmentation, which may not be accurate. An example of a successful CAD system would be one that uses geometrical-model-based features to classify each voxel (elements in a volume that constitute a 3D space) in order to scan each module (Shuchao & Du, 2017). While these systems have proven effective, a considerable number of nodules could still potentially go undetected. Machine learning has proven very effective in discovering discriminative features and using this to boost the accuracy of many visual recognition systems. To utilize machine learning, a large amount of training data is necessary. This is because the more information is given, the more information the recognition system has to work off of, and specifically in this scenario, evaluate what is harmful.

Purpose

The purpose of this study was to evaluate the most effective method of lung cancer diagnosis, and evaluate whether the use of CNNs could be beneficial to a lung cancer diagnosis. The implementation of new methods of a lung cancer diagnosis is essential to the survival of future lung cancer patients. In many cases, deaths that are caused by lung cancer could have been avoided if the individual had gotten their lung cancer diagnosis and treatment fast enough. With convolutional neural networks, speed is less of an issue compared to current methods, as artificial intelligence can find scan and diagnose lung cancer far faster than humans can. Current methods of diagnosis, including chest X-rays, standard computed tomography scans, and sputum cytology require more time to produce scan results and are possibly inaccurate (Raykar 2016). To date, research lacks in determining whether CNNs are more effective when compared to other, more conventional methods of diagnosing lung cancer. This paper will compare the effectiveness of the more conventional methods of diagnosing lung cancer to the method of using CNNs in combination with CT scans.

Research Questions

Is the use of CT scans with CNN a more effective method of diagnosis, to be used as an alternative to currently used methods?

Null Hypothesis

Using convolutional neural networks in combination with computed tomography scans is not beneficial enough to be used currently due to yielding a high amount of false positives.

Alternative Hypothesis

The use of convolutional neural networks in combination with computed tomography scans is beneficial enough, compared to the speed and accuracy of other scans, to be implemented currently.

Methods

Data Sources

In order to form my conclusions based on the research topic, research was conducted on sources from online databases, such as Google Scholar, Elsevier, PUBMED-NCBI, ResearchGate, ScienceDirect, Wiley Interstate Journals, etc… Search terms including convolutional neural networks, computed tomography scans, lung cancer, artificial intelligence, and cancer diagnosis were used in order to acquire the most applicable information and data.

Systematic Literature Review

Systematic literature review was the most suitable method of research and data collection because using CNN to diagnose lung cancer is a fairly new method of diagnosing lung cancer, so there was not enough data to conduct meta-data analysis. However, the literature presents substantial information/data for the diagnosis method, and findings can be shown through the use of a systematic literature review.

Inclusion and Exclusion Criteria

All papers used for this research were full text, peer-reviewed scholarly articles. Papers were excluded if written more than ten years ago unless they included background information that was still applicable to the research. However, data from sources more than ten years old were excluded from the collection, subsequent calculations.

Furthermore, papers were excluded based on the type of artificial intelligence that may have been used in the research paper’s experiments. While I did search for papers using keywords such as artificial intelligence and lung cancer, I excluded papers that did not focus on convolutional neural networks, in order to create a focus for the research. When narrowing down which form of artificial intelligence to use, I decided on using convolutional neural networks because CNN boasts the best respective statistics concerned with false positive rates and sensitivity rates, compared to other forms of artificial intelligence. As well as that, an abundance of research was already done concerning CNN because of its beneficial properties, leaving a gap for me to analyze the benefits of using this new technology in lung cancer detection, compared to other methods of detection such as chest X-rays.

Moreover, the data gathered for this research was limited to examining studies that focused on methods of detecting lung cancer. Papers may have been used for background information collection, but were excluded from use in data collection if they focused on other types of cancer or diseases, such as breast cancer. Because the data compiled was from sources focusing on convolutional neural networks and chest X-rays detecting lung cancer, this allowed me to focus my data collection. By focusing the data collection, this allowed for collecting unbiased data that focused on research done within similar, if not the same, parameters. Papers that may have had conflicting interests based on the authors or inconsistent variables that didn't align with the rest of the data and information that I was collecting were left out of the paper, in order to not skew the results.

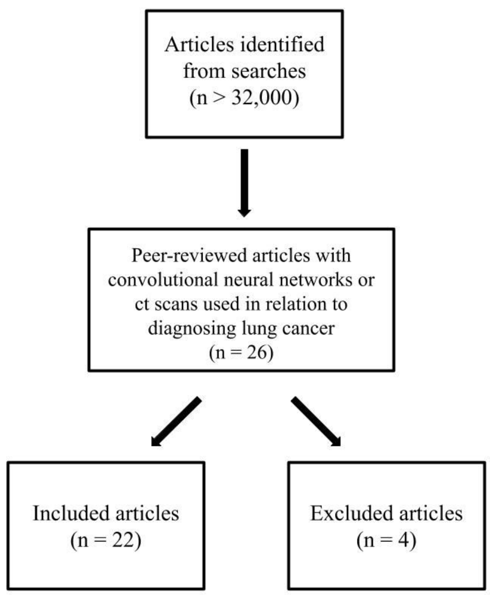

Fig. 4. A diagram of the flow of studies during the systematic literature review.

Data Extraction

The sensitivity rates and false positive rates of convolutional neural networks were compared with the sensitivity rates and false positive rates of chest x-Rays, over multiple different trials, in order to compare the widest variety of data. This allowed for less probability that results from my research could be statistical anomalies, or made by chance.

The raw data that was extracted was taken of percentages of their respective test study size. In order to compile the data within even parameters, I took the percentages and transferred the percentages into total members of a population. For example, if there was a sensitivity rate of 80.2% out of a population of 500 test subjects, then that means that 401 of the test subjects were had their lung cancer correctly detected. By doing this, it allowed me to formulate total sensitivity rates and false positive rates, that were formed with equal parameters, and also combined many papers.

Statistical Analysis

The effectiveness of convolutional neural networks and chest X-rays was evaluated and compared by observing the sensitivity rates and false positive rates concerned with their respective method of lung cancer detection. Paired sample t-tests were run on each study using Microsoft Excel's' Data Analysis Toolpak to calculate the significance of the differences in sensitivity rates or false positive rates. The t-tests allowed me to determine the validity of the research because by doing t-tests, they give p-values. These p-values show the probability that there was a significant difference. In the science field, the widely accepted value for the margin of significance is a p-value $\leq .05$, showing that the differences were significant and the null hypothesis would be rejected. This means that there is a less than 5% chance that the data extracted was created by random chance.

Results

Table 1. This depicts the sensitivity of CNN w/ CT Scans, as well as the false positive rate, conducted over multiple trials (Huang et al., 2017; Gould et al., 2013; Khosravan and Bagci, 2018; Pang et al., 2018; Vivek, 2014; Toyoda et al., 2018; Golan, 2018).

Lung Cancer Detection Frequency with CNN with CT Scans	Rate of False Positives with CNN with CT Scans
83.4%	8.3%
85.6%	7.6%
86.2%	8.2%
83.8%	6.7%
80.9%	6.6%
88.3%	9.3%
84.8%	5.5%
86.5%	8.7%
83.3%	5.9%
85.7%	8.1%
85.6%	9.2%
87.4%	6.8%

88.9%	7.4%
83.4%	8.7%

Table 2. This table depicts the sensitivity rates, as well as the false positive rates of chest X-rays, evaluated over multiple trials (Huang et al., 2017; Gould et al., 2013; Khosravan and Bagci, 2018); Toyoda et al., 2018; Hou 2018; Ginneken, 2016).

Lung Cancer Detection Frequency with Chest X-rays	Rate of False Positives with Chest X-rays
76.3%	11.3%
75.7%	9.2%
76.2%	12.1%
78.0%	14.2%
79.1%	10.2%
73.2%	9.6%
76.7%	10.8%

77.6%	7.9%
76.5%	11.6%
76.9%	12.3%
72.6%	13.2%
78.1%	9.6%
76.8%	8.9%
80.1%	13.5%

Fig. 5. This graph shows a comparison of the sensitivity rates between chest X-rays and CNN w/ CT scans.

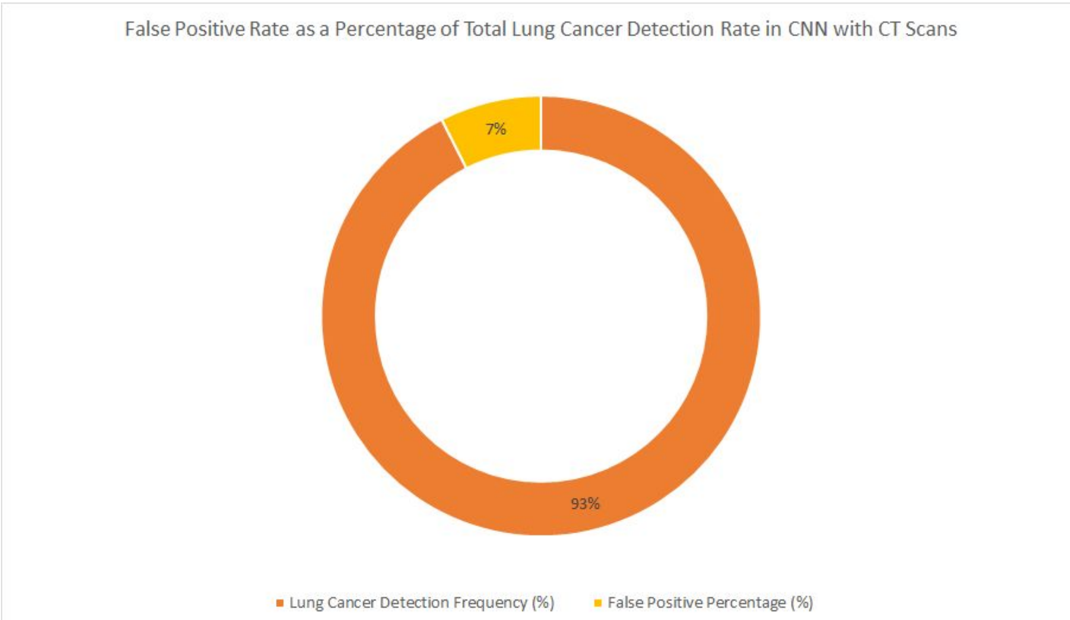

Fig. 6. This graph shows the average false positive rate as a percentage of the total amount of lung cancer detections made by CNN with CT scans

The sensitivity, which depicts how often the methods will diagnose lung cancer, is essential to the diagnosis of lung cancer, with the higher percentages being the best. As shown in table one, over fourteen trials, the sensitivity rate of CNN with CT scans fluctuate between a range of 80.9% and 88.9%. In addition, the false positive rates fluctuate between a range of 5.5% and 9.2%. In comparison, Table 2 shows the sensitivity rate and false positive rate of more conventional treatment, chest X-rays, over the same amount of trials. The range of the sensitivity rates of chest X-rays is shown to be between a range of 72.6% and 80.1%, while the false positive rates are between 7.9% and 14.2%. Fig. 5 depicts a comparison between the two methods, showing the average sensitivity rate of CNN w/ CT scans to be around 84.4%, while the average sensitivity rate of chest X-rays is around 76.9%. This indicates a 7.5% difference in the average sensitivity rates between the two methods of lung cancer detection. Fig. 6 shows one of the main drawbacks of CNN w/ CT scans, a relatively high false positive rate. However, chest X-rays have a higher false positive rate, at an average of 11.1% false positive rate. The data from the different trials was compiled by adding together the total number of participants from each trial, in order to conduct a t-test and find a p-value. The given p-value from doing this statistical analysis gave a p-value of .0411.

Discussion

When comparing CNN with CT scans and chest X-rays, it is apparent that CNN in combination with CT scans has greater benefits than other methods of lung cancer detection. Its average sensitivity rate was about 7.5% higher compared to the most popular method of detecting lung cancer, as indicated by tables 1 and 2. This suggests that CNN with CT scans can be highly beneficial in getting accurate lung cancer detection readings to patients as fast as possible. However, the sensitivity rate of a scan conducted by artificial intelligence, such as CNN, must be far closer to a total of 100%, in order to be considered relevant in comparison to using chest X-rays. This is because, while chest X-rays can have their results reviewed by humans, who can review data multiple times, CNN can only use data that is provided to it. Additionally, humans would not be checking the diagnosis results of the CNN because adding in humans to check the results would compromise the speed at which CNN can deliver results, which is one of the main reasons why this method of cancer detection is so appealing. Similarly, indicated by tables 1 and 2, CNN with CT Scans has a 3.6% lower false positive rate in comparison to chest X-rays. However, mistakes in chest X-rays can be reevaluated and corrected, while mistakes that CNN makes cannot be corrected easily unless new information is relayed to the CNN, or a human reviews the detection results. In either case, this could compromise the speed at which CNN makes its diagnosis, making it not beneficial to implement it currently. After compiling all of the data together, based on the total number of participants and percentages of false positive rates, sensitivity rates, conducting a t-test to test the hypotheses, a p-value of .0411 was obtained. Being lower than a p-value of .05, this indicates that the null hypothesis should be rejected, and the alternative hypothesis should be accepted supporting the benefit of CNN w/ CT scans. A p-value of .0411 indicates that there is only a 4.11% chance that using the data given, rejecting the null hypothesis and accepting the alternative hypothesis would be a mistake.

Sources of Error

Sources of error in this study include different parameters that may have been used to conduct the different trials with CNN w/ CT scans, such as using different databases to detect malignant growth and different focuses of the peer-reviewed papers that were gathered for data and statistical analysis. This could include observing the effectiveness of different forms of artificial intelligence, and what the researchers that developed the artificial intelligence classify as malignant growth. This means that what some CNN could see as signs of lung cancer, other CNN, which could be feeding their results through different parameters, may see no signs of lung cancer.

Conclusion

Overall, the systematic literature review conducted on this research supports the hypothesis that convolutional neural networks in combination with computed tomography scans are not currently beneficial enough to be widely implemented in place of current methods of diagnosis. While CT w/ CNN scans look like an appealing option, the overall speed and efficiency of the artificial intelligence system are offset by the lack of credibility and potential for life-threatening mistakes. While adding a scientist to observe the findings of the AI and check to make sure everything is correct, that would compromise the speed, which makes this method of diagnosis appealing, to begin with. For those reasons, while CNN w/ CT scans are a very appealing option, more research must be done on them, in order to ensure that they are safer than current options before they can be widely implemented into society.

Further Work

To further contribute to this research, research analyzing more variables that can be applied to the comparison between convolutional neural networks and chest X-rays. These variables could include more qualitative data, including ethical concerns related to having artificial intelligence making important decisions, such as detecting and diagnosing cancer. As of the creation of this research, there is little legislation in place concerning the ethical responsibilities concerned with artificial intelligence in the medical field. As well as that, more quantitative data could be analyzed in order to more clearly establish which method of lung cancer detection is more effective. This data could be data concerned with speed, as I didn’t elaborate heavily on the speed aspect of lung cancer diagnosis because convolutional neural networks far exceeded the speed of humans evaluating the lung cancer scans, so data collection concerned with it wouldn't reveal any new revelations. As well as speed, other variables such as false negative rates between the two could be evaluated. False negatives are potentially even more harmful than false positives, however, there were fewer data concerning them because they happen less frequently than their counterpart.

Furthermore, there could be more comparisons created with different methods of lung cancer detection, such as normal CT scans, sputum cytology, and tissue samples. Many methods of lung cancer detection have an abundance of research on them. However, they are used in niche ways due to their higher costs, and lower speeds. That being said, there is an argument to be made about their benefits when concerned with false positive rates and sensitivity rates because the less commonly used methods usually have a higher accuracy to compensate for their slow speeds.

Moreover, there are more applications of artificial intelligence in the medical field than researched in this paper. Especially in the detection of other cancers, such as breast cancer or colon cancer, the integration of artificial intelligence could be highly beneficial to the improvement of their detection methods. While there is already research concerning artificial intelligence and its integration into many of these cancers because of how common they are, a statistical analysis similar to what was done with this research could be done concerning other methods of cancer in order to interpret what the most effective method of detecting other types of cancer is.

Additionally, because convolutional neural networks is still a developing technology, data concerned with it actually being applied to test real patients that needed a lung cancer evaluation was unavailable. As CNNs and other methods of AI become more refined, there will no doubt be more rules and regulations put in place that would allow for their application in the medical field. Artificial intelligence like CNN is always being innovated and developed, so further work could be done with the AI discussed in this research is improved upon, or there is another form of AI that is superior to CNN.

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