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Comparison of Convolutional Neural Networks and Support Vector Machines on Medical Data: A Review

Furizal [a,1], Alfian Ma'arif [b,2,*], Dianda Rifaldi [c,3], Asno Azzawagama Firdaus [c,4]

[a] Department of Informatics Engineering, Universitas Islam Riau, Pekanbaru, Indonesia
[b] Department of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
[c] Master Program of Informatics, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
[1] furizal.id@gmail.com; [2] alfianmaarif@ee.uad.ac.id; [3] diandarifaldi@gmail.com; [4] asnofirdaus@gmail.com
* Corresponding Author

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ABSTRACT

Medical image processing has become an integral part of disease diagnosis, where technological advancements have brought significant changes to this approach. In this review, a comprehensive comparison between Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) in processing medical images is conducted. Automated medical analysis is becoming increasingly important due to issues of subjectivity in manual diagnosis and potential treatment delays. This research aims to compare the performance of Machine Learning (ML) in medical contexts using MRI, CT scan, and X-ray data. The comparison includes the accuracy rates of CNN and SVM algorithms, sourced from various studies conducted between 2018 and 2022. The results of the comparison show that CNN has higher average accuracy in processing MRI and X-ray data, with average values of 98.05% and 97.27%, respectively. On the other hand, SVM exhibits higher average accuracy for CT scan data, reaching 91.78%. However, overall, CNN achieves an average accuracy of 95.58%, while SVM's average accuracy is at 94.72%. These findings indicate that both algorithms perform well in processing medical data with high accuracy. Although based on these average accuracy rates, CNN demonstrates slightly better capabilities than SVM. Further research and development of more complex models are expected to continue improving the effectiveness of both approaches in disease diagnosis and patient care in the future.

1. Introduction

In the medical field, patient diagnosis and treatment are at the core of practices conducted by healthcare professionals, such as doctors and other medical personnel [1], [2]. Through careful diagnostic processes and the use of various diagnostic tools, doctors aim to identify diseases or health disorders that patients may be experiencing [3], [4]. After a diagnosis is established, doctors then design appropriate treatment plans, which may include medical treatment, surgical intervention, physical therapy, or palliative care, depending on the specific conditions of the patient. In this technological era, some medical decisions are based on diagnostic images, such as Magnetic Resonance Imaging (MRI) [5]-[9], Computed Tomography (CT) scans [7], [10]-[12], and X-ray images [13]-[16]. These images can provide invaluable information in disease diagnosis, treatment planning, and patient monitoring.

Interpreting and classifying these medical images manually can have some drawbacks, although manual diagnosis by doctors has become a common practice in the medical world [17]. One major issue is the subjectivity and variation among individuals in assessing and interpreting symptoms and medical test results. Additionally, the manual diagnostic process can be time-consuming, especially in complex or rare cases, which can delay appropriate treatment and potentially reduce the effectiveness of medical interventions. Furthermore, there is also a possibility of human errors, such as fatigue, workload pressure, or negligence, which can affect the accuracy and consistency of diagnoses [18]-[20]. Therefore, the integration of artificial intelligence (AI) and ML technology in medical analysis is becoming increasingly important to help address these issues by providing more objective, rapid, and accurate diagnostic tools for various diseases and health disorders.

Comparing ML methods in the classification of medical images becomes an important endeavor. By comparing ML approaches, it will be possible to evaluate the strengths and weaknesses of each method being compared. This will assist doctors and researchers in selecting the most suitable approach to meet specific needs in the classification of medical images. The importance of this research is not only limited to the ability to classify medical images with high accuracy but also in improving efficiency and speed in the diagnosis and treatment process. By using appropriate ML methods, it is possible to expedite the classification process of medical images, thus enabling doctors to make faster and more accurate decisions in patient care.

This paper aims to present a comprehensive overview and comparison of CNN [5], [13], [21], [22] and SVM [23]-[26] methods that have been applied in the processing of medical images by previous studies. By analyzing a number of related studies, this paper will identify the CNN and SVM methods that have been used, evaluate the advantages and limitations of each method, and provide insights into the latest advancements in the use of this technology in a medical context. CNN and SVM methods are chosen for comparison in this paper because many researchers use these methods in medical data processing [5], [6], [15], [26], [27]-[32]. This will be valuable and contribute to providing insights to researchers about method selection for future research. Through this review, it is hoped that this paper will also provide a better understanding of the potential, challenges, and future research directions in the use of ML, particularly in CNN and SVM methods for processing medical images.

2. ML Methods Compared

ML as a branch of AI, enables systems to learn from data without being explicitly programmed. This gives machines the ability to recognize patterns in data and make decisions or predictions without direct human intervention. By leveraging algorithms and statistical models, ML can improve its performance as it gains experience and processes more data. The application of ML in the medical field holds great potential to enhance diagnosis, disease prediction, and patient management. By analyzing large and diverse medical data, ML can assist doctors in identifying relevant patterns in patient data, predicting disease progression, and even aiding in individually tailored treatment plans. In ML, there are many algorithms that can be used in processing medical data, including CNN and SVM.

2.1. CNN Method

CNN is a type of deep learning model [33] that has become dominant in various computer vision tasks and attracted interest in various domains, including the medical field [34]-[36]. CNNs are designed to automatically and adaptively learn spatial feature hierarchies through backpropagation using several building blocks, such as convolutional layers, pooling layers, and fully connected (FC) layers [37]-[39]. Two challenges in applying CNNs to medical tasks are small datasets and overfitting. CNNs can process data that have grid patterns [40], such as images, and are inspired by the organization of the visual cortex in animals. They are designed to automatically and adaptively learn spatial feature hierarchies, from low-level to high-level patterns. Convolutional and pooling layers perform feature extraction, while the FC layers map the extracted features to the final output, such as classification [41]-[43]. The convolution operation plays a key role in CNNs, where a kernel is applied to each position of the image to extract features, making CNNs highly efficient for image processing [44]. The training process of CNN models involves adjusting parameters such as kernels through the backpropagation algorithm and gradient descent optimization. An overview of the architecture of CNNs is generally depicted in Fig. 1.

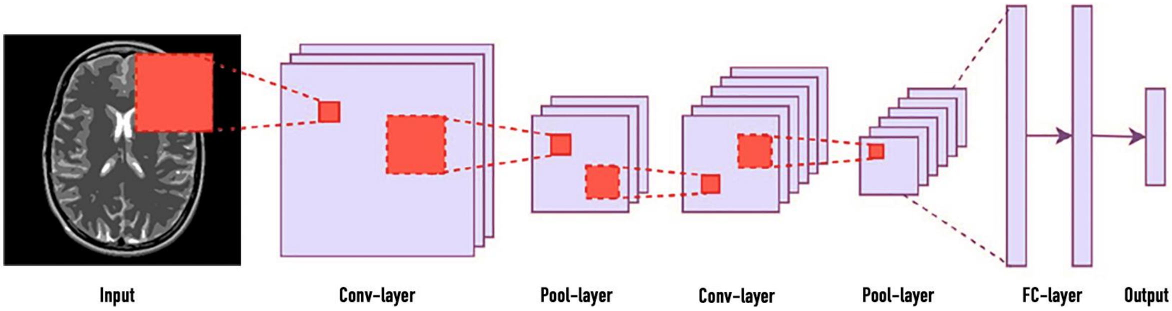

Fig. 1. CNN architecture [45]

2.2. SVM Method

SVM is a ML algorithm that is fundamentally linear but flexible enough to handle classification and regression problems [46]. SVM can form classifiers for classification problems and regressors for regression problems. However, the SVM classifier is the core of the SVM concept and is generally the most suitable algorithm for solving classification problems [47]-[50].

Although SVM is fundamentally a linear algorithm, its concept is very strong in handling non-linear problems [51]. By creating a hyperplane in an N-dimensional space [52], the SVM classifier divides data points belonging to two separate classes. SVM uses the concept of margin to determine the hyperplane, with Support Vectors helping to orient it [53]. Thanks to its ability to handle non-linear problems, SVM has become an effective tool in various fields, including in medical data analysis. An overview of the architecture of SVMs is generally depicted in Fig. 2.

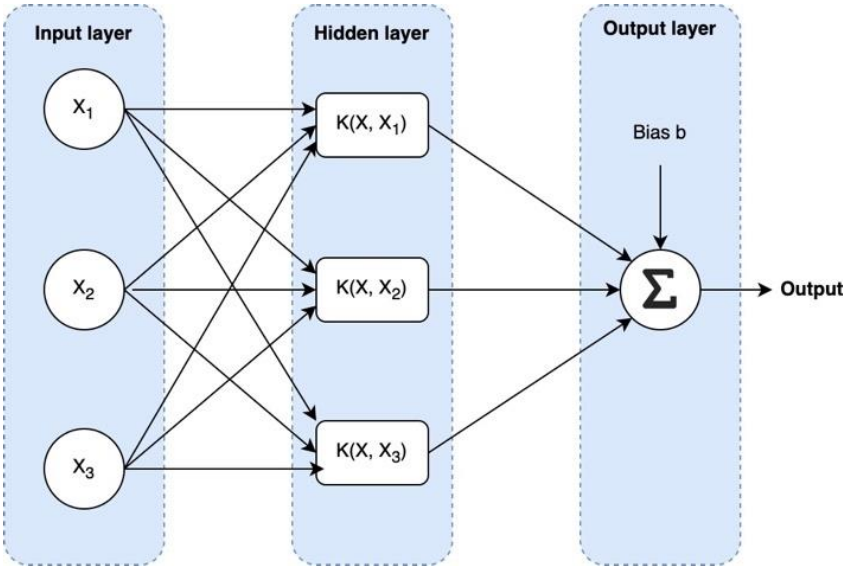

Fig. 2. SVM architecture [54]

3. Dataset

The comparison of CNN and SVM performance is based on three different datasets: MRI Dataset, CT scan, and X-Ray. These datasets are sourced from various institutions and organizations worldwide. The main sources of data include Radiopaedia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015 testing dataset, as well as the ADNI (Alzheimer's Disease Neuroimaging Initiative) website. Additionally, the dataset includes data from various hospitals such as Basavatarakam Cancer Institute in Hyderabad, Nanfang Hospital and General Hospital, Iraq Teaching Oncology Hospital/National Cancer Center Directorate (IQ-OTH/NCCD), and Department of Oncology, Manipal Hospital, and Vijayawada. Other sources of data include research findings from various conferences such as the International Conference on Computational Intelligence and Data Science (ICCIDS 2019), as well as specific studies mentioned like the Zhao et al. dataset and Italian Society of Medical and Interventional Research dataset. The sources of data are widely dispersed, including from GitHub repositories, official websites like Kaggle, as well as online publications and data repositories from institutions like IEEE Data Port.

3.1. MRI Dataset

The MRI dataset is a collection of medical image data generated using MRI technology [8], [55]-[57]. Each image in this dataset represents the internal structure of the human body recorded using magnetic resonance and radio waves [58]-[60]. This dataset typically consists of a series of slice images in three dimensions covering various parts of the body, such as the brain, spine, joints, and other internal organs [7], [61]. Each MRI image in this dataset may vary in settings, such as slice thickness, spatial resolution, and image contrast, which can affect the quality and information that can be obtained from the image [62]-[64]. MRI datasets are commonly used in various research and applications, including medical diagnostics, scientific research, imaging technology development, and ML model training for pattern recognition and medical image analysis. Most MRI datasets are available in digital format and can be accessed through various sources, including online repositories, medical databases, and open research projects that share data for scientific and clinical purposes [65]-[68].

3.2. CT Scan

CT scan is a highly important and beneficial medical imaging method that supports diagnosis, especially in obtaining detailed images of body organs [69], [70]. Unlike MRI technology, which uses radio waves and magnets [71], [72], CT scan utilizes X-rays and computer technology to produce images of body organs from various angles [73], [74]. The CT scan process is often necessary in diagnosing various abnormalities or diseases in the body, including head injuries, issues with vital organs such as the heart and lungs, and for monitoring the progression of certain medical conditions such as tumors or blood clots. CT Scan has several advantages, including its ability to provide rapid results, clear and specific images, and relatively lower costs compared to some other imaging methods.

Additionally, CT scan also requires some preparations and precautions to be taken before undergoing the procedure, such as fasting for several hours beforehand and ensuring the body is free from metallic objects. Although CT scan involves a low risk of radiation exposure, the procedure is generally considered safe and does not cause long-term side effects. Therefore, CT scan remains one of the important imaging methods in the medical field to assist doctors in diagnosing and planning patient treatment accurately and effectively.

3.3. X-ray

X-ray, also known as radiography, is one of the vital methods in the medical field that utilizes X-ray radiation to produce images of organs inside the body [14], [75]. This process plays a crucial role in assisting doctors in establishing accurate diagnoses for patients. Typically, X-rays are performed to evaluate bone and joint conditions, such as fractures, joint inflammation, tooth decay, osteoporosis, and even bone cancer. However, its utility also extends to other areas, including examining soft organs like the lungs, breasts, heart, and digestive tract. X-rays are also used in other imaging procedures such as CT scans and fluoroscopy.

Despite being an essential tool in the medical field, the use of X-rays is not without risks. Exposure to radiation during X-ray procedures carries potential risks, especially for patients receiving high doses of radiation or pregnant women. Frequent X-ray examinations also have the potential to damage the DNA of body cells, although this risk is generally considered low. However, the risk may increase for certain patients, such as children, pregnant women, and those with specific genetic conditions. Additionally, the use of contrast agents in X-rays can also lead to side effects, such as dizziness, nausea, or even serious allergic reactions like anaphylactic shock.

4. Analysis of Selected Studies

The selected studies in this summary primarily focus on disease detection such as brain tumors, lung cancer, pneumonia, and COVID-19 using ML algorithm techniques such as CNN and SVM. The summarized studies range from previous research published between 2018 and 2022, comprising a total of 32 studies, including CNN-MRI (5 studies), SVM-MRI (7 studies), CNN-CT scan (5 studies), SVM-CT scan (5 studies), CNN-X-ray (5 studies), and SVM-X-ray (5 studies).

J. Seetha and S. Selvakumar Raja, researched Brain Tumor Classification Using MRI image data CNN in September 2018 [76]. This study proposed an automated approach, demonstrating 97.5% accuracy with low complexity in classifying brain tumors, compared to other existing methods. T. Hossain et al. in 2019 also discussed brain tumor detection using CNN with MRI data [77]. The proposed method involved segmentation using Fuzzy C-Means clustering and classification using CNN. CNN classification achieved an accuracy of 97.87%. This study demonstrates the effectiveness of CNN in detecting brain tumors from 2D MRI images. Furthermore, other researchers such as A. W. Salehi et al. also discussed the use of CNN for early diagnosis and classification of Alzheimer's disease using MRI images. The achieved accuracy results were quite high, reaching 99% [30]. From these three studies related to CNN using MRI data, it is evident that CNN can provide excellent results in processing MRI data with high accuracy.

In addition to MRI, CNN has also been tested using other medical data such as CT scans. Many researchers have explored various cases. One example is H. F. Al-Yasriy et al. in 2020, who used CNN in processing CT scan data to detect lung cancer. The data used was obtained from Iraq Teaching Oncology Hospital/National Cancer Center Directorate (IQ-OTH/NCCD). The results were quite high with an accuracy of 93.55% [28]. Then, in the same year, A. Krishna et al. also studied lung cancer detection using CT scan data and achieved an accuracy of 94.5% [29]. Meanwhile, in the following year, N. K. Mishra et al. used CT scans for Covid-19 detection and achieved a higher accuracy of 99% [78]. These achievements also demonstrate the excellent potential and capability of CNN in processing CT scan data.

For X-ray data, CNN has also been used for various purposes, such as detecting bacterial infections, pneumonia, and Covid-19. In 2020, H. Sharma et al. attempted to apply CNN to process X-ray data obtained from the Kaggle website. This study aimed to detect pneumonia. The results were quite good with an accuracy of 90.68% [79]. Then, in the same year, T. Rahman et al. also used CNN for detecting bacterial and viral pneumonia using X-ray data obtained from Kaggle. The results achieved a higher level of accuracy compared to those obtained by Sharma et al. [79], reaching 98% [80]. Not stopping there, other researchers, A. A. Reshi et al., also conducted research using X-ray data in 2021 [13]. This study aimed to detect Covid-19. The results were also very satisfying, with an accuracy rate of 99.5%.

In addition to CNN, SVM also serves as one of the main algorithms in processing medical data such as MRI, CT scans, and X-rays. This was demonstrated by A. Hussain and A. Khunteta in 2020, who researched the application of SVM in processing MRI data obtained from the Kaggle website and Figshare for brain tumor detection, achieving a high accuracy of 93.05% [24]. Furthermore, this research is also supported by other researchers such as M. A. Ansari et al. in the same year and the same case, achieving an accuracy of 98.91% [32]. Then, Z. Jia and D. Chen also contributed to supporting the reliability of SVM in processing MRI image data with an accuracy of 98.51% [81]. The results obtained by these three studies [24], [32], [81] are sufficient to prove the reliability of SVM in processing MRI data.

On the other hand, SVM also makes significant contributions to processing CT scan data. In 2021, A. Rehman et al. researched lung cancer detection using SVM by processing CT-scan data [82]. This study achieved an accuracy of 93%, which is quite substantial. Furthermore, in the same year, M. A. Alzubaidi et al. also investigated the same case [12]. However, the data used were sourced from The Cancer Imaging Archive (TCIA) database, different from the data used by A. Rehman et al. [82]. The accuracy obtained was higher, reaching 97%. Additionally, other researchers like M. Singh et al. also contributed by obtaining CT scan data from various sources, with an accuracy of 95.7% [83].

Additionally, SVM is often used to process X-ray data for various purposes, such as detecting Covid-19, pneumonia, and others. The results produced by SVM are also very good. This is supported by research conducted by A. M. Sarhan [15] in 2020. This study aimed to detect Covid-19 by processing X-ray data obtained from the GitHub repository by Cohen JP and the Chest X-ray8 database by Wang et al. The study obtained an accuracy of over 90%, specifically 94.5%. Then, another study in the same year by D. F. Eljamassi and A. Y. Maghari [84] achieved a higher accuracy of 98.14%. In the following year, several studies also yielded high results, ranging from 94.88% to 99.17% [16], [85], [86]. A summary of previous research on the application of CNN and SVM methods to medical data is shown in Table 1.

Table 1. Previous research on the application of CNN and SVM methods to medical data (MRI, CT scan, and X-Ray)

Ref.	Algo-rithm	Research Objective	Year	Data-set	Data Source	Accu-racy (%)
J. Seetha and S. S. Raja [76]	CNN	Brain tumor detection	2018	MRI	Radiopaedia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015 testing dataset	97.50
T. Hossain et. al [77]	CNN	Brain tumor detection	2019	MRI	Department of Computer Science and Technology, Ahsanullah University of Science and Technology, Dhaka, Bangladesh	97.87
V. R. Sajja and H. K. Kalluri [23]	CNN	Brain tumor detection	2020	MRI	BRATS database	96.15
A. W. Salehi et. al [30]	CNN	Diagnosis and classification of Alzheimer's Disease	2020	MRI	ADNI (Alzheimer's Disease Neuroimaging Initiative) website	99.00
A. Chattopadhyay and M. Maitra [5]	CNN	Brain tumor detection	2022	MRI	Not mentioned in detail	99.74
A. Hussain and A. Khunteta [24]	SVM	Brain tumor detection	2020	MRI	The websites www.kaggle.com and www.figshare.com	93.05
M. A. Ansari et. al [32]	SVM	Brain tumor detection	2020	MRI	Hospital	98.91
Z. Jia and D. Chen [81]	SVM	Brain tumor detection	2020	MRI	Not mentioned in detail	98.51
B. Jabber et. al [26]	SVM	Bone cancer detection	2020	MRI	Basavatarakam Cancer Institute, Hyderabad	92.00
D. Bansal et. al [87]	SVM	Dementia brain disease detection	2020	MRI	International Conference on Computational Intelligence and Data Science (ICCIDS 2019) dan ADNI database	93.00
M. Shahajad et. al [88]	SVM	Brain tumor detection	2021	MRI	Website Kaggle	92.00
N. Bhagat and G. Kaur [6]	SVM	Brain tumor detection	2022	MRI	Nanfang Hospital and General Hospital	99.24

Ref.	Algo-rithm	Research Objective	Year	Data-set	Data Source	Accu-racy (%)
H. F. Al-Yasriy *et. al* [28]	CNN	Lung cancer detection	2020	CT scan	Iraq Teaching Oncology Hospital/National Cancer Center Directorate (IQ-OTH/NCCD)	93.55
A. Krishna *et. al* [29]	CNN	Lung cancer detection	2020	CT scan	Department of Oncology, Manipal Hospital, and Vijayawada.	94.50
M. Polsinelli *et. al* [21]	CNN	"Identifying CT images of COVID-19 and non-COVID-19 lungs	2021	CT scan	Two main sources: Zhao et al. dataset and Italy dataset	85.03
N. K. Mishra *et. al* [78]	CNN	Detecting COVID-19	2021	CT scan	Authentic websites: https://www.kaggle.com/, https://www.sirm. org/, and https://radiopaedia.org/	99.00
P. gifani *et. al* [11]	CNN	Detecting COVID-19	2021	CT scan	The publicly available COVID19-CT dataset	85.00
Q. Firdaus *et. al* [10]	SVM	Lung cancer detection	2020	CT scan	Not mentioned in detail	83.33
H. F. Kareem *et. al* [25]	SVM	Lung cancer detection	2021	CT scan	The Teaching Oncology Hospital and National Center for Cancer Diseases in Iraq	89.89
M. A. Alzubaidi *et. al* [12]	SVM	Lung cancer detection	2021	CT scan	Database TCIA (The Cancer Imaging Archive)	97.00
A. Rehman *et. al* [82]	SVM	Lung cancer detection	2021	CT scan	AI and Data Analytics Lab CCIS Prince Sultan University Riyadh Saudi Arabia	93.00
M. Singh *et. al* [83]	SVM	Detecting COVID-19	2021	CT scan	(a) Zhao et al. for D1 [89], (b) Cohen, Morrison, and Dao for D2, and (c) Italian Society of Medical and Interventional Research for D3.	95.70
H. Sharma *et. al* [79]	CNN	Pneumonia detection	2020	X-ray	Website Kaggle	90.68
T. Rahman *et al* [80]	CNN	Detecting bacterial and viral pneumonia	2020	X-ray	Database Kaggle chest X-ray pneumonia	98.00
A. A. Reshi *et al* [13]	CNN	Detecting COVID-19	2021	X-ray	GitHub repository and IEEE Data Port, as well as from hospitals and clinics	99.50
S. Hira *et. al* [22]	CNN	Distinguishing COVID-19 from viral pneumonia, bacterial pneumonia, and normal cases	2021	X-ray	GitHub repositories, online publications, websites, or directly from PDFs	99.32
P. M. de Sousa *et al* [27]	CNN	Detecting COVID-19	2022	X-ray	COVID-19 image data collection, ChestXray14 repository, and BIMCV COVID-19+ repository	98.84
A. M. Sarhan [15]	SVM	Detecting COVID-19	2020	X-ray	GitHub repository: https://github.com/ieee8023/COVID-chestxraydataset by Cohen JP and the Chest X-ray8 database by Wang et al.	94.50
D. F. Eljamassi and A. Y. Maghari [84]	SVM	Detecting COVID-19 infection, pneumonia, or health	2020	X-ray	GitHub and Kaggle websites.	98.14

Ref.	Algo-rithm	Research Objective	Year	Data-set	Data Source	Accu-racy (%)
K. Garlapati *et. al* [85]	SVM	Detecting COVID-19	2021	X-ray	Publicly available sources (repositories), not specifically mentioned in the text.	99.17
S. Samsir *et. al* [86]	SVM	Detecting COVID-19	2021	X-ray	Kaggle website and from various sources, including licensed clinical laboratories	98.00
J. N. Hasoon *et al* [16]	SVM	Detecting COVID-19	2021	X-ray	GitHub repository shared by Cohen et al [90]	94.88

5. Comparison of CNN and SVM Methods

The CNN method is widely used for brain tumor detection with high accuracy, as demonstrated by studies involving MRI datasets from various sources, including Radiopaedia, BRATS, and ADNI. The classification accuracy obtained ranges from 96.15% to 99.74%, indicating the effectiveness of CNN in addressing detection issues in brain MRI images. Additionally, SVM is also commonly used for brain tumor detection with promising results, although some studies show slightly lower accuracy compared to CNN. Several studies also explore lung cancer and COVID-19 detection using CT scan and X-ray data. The findings indicate that SVM can be effectively used to detect lung cancer and COVID-19 with accuracy reaching up to 99.17% [85].

In studies of COVID-19 detection using X-ray, datasets vary from sources such as Kaggle, GitHub, and other public repositories. In some cases, the use of different datasets can affect detection accuracy, but overall, the results obtained show that ML techniques with CNN and SVM methods can be effective tools in identifying COVID-19 cases. However, to provide a distinction, the accuracy rates between CNN and SVM have been presented in Fig. 3, Fig. 4, Fig. 5. Fig. 3 compares CNN and SVM for MRI data processing, Fig. 4 for CT scan data, and Fig. 5 for X-ray. These graphs will serve as the basis for obtaining a comparison between these two methods.

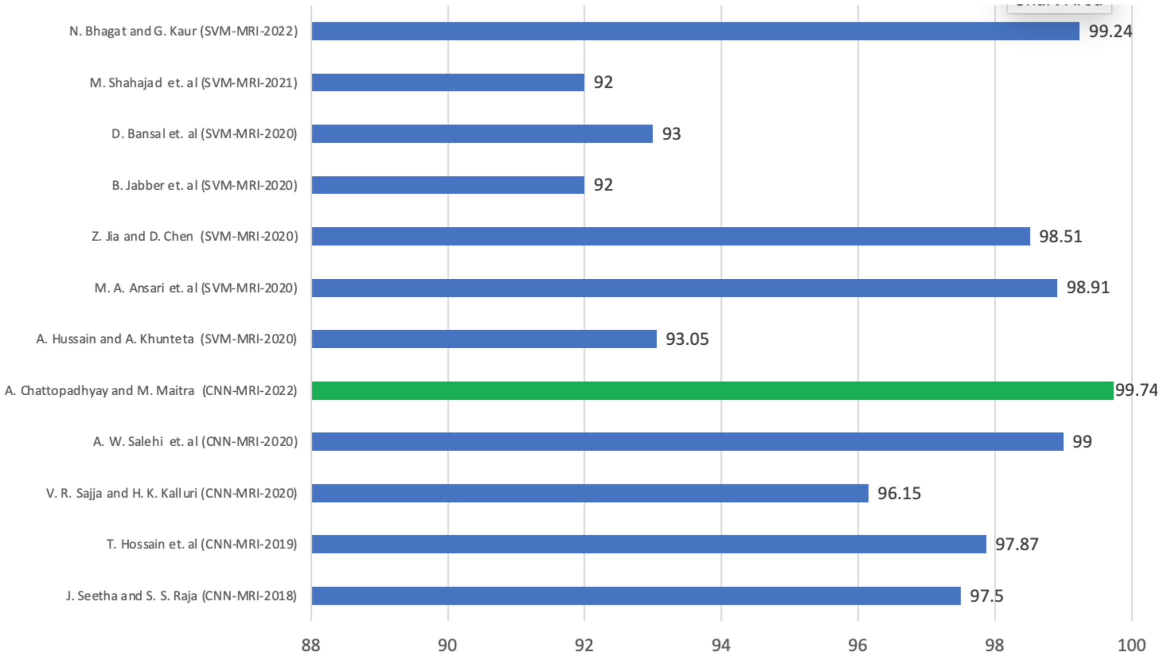

Fig. 3. Comparison of accuracy between previous studies on MRI data using CNN and SVM methods

Fig. 3 shows that both algorithms, CNN and SVM, provide equally high results in processing MRI data. CNN achieves accuracy between 96.15% and 99.74%, while SVM achieves accuracy between 92% and 99.24%. The results obtained by SVM are slightly lower compared to CNN. However, both have good capabilities, which only show minor differences in accuracy.

In Fig. 4, CNN and SVM in processing CT-scan data yield lower accuracy compared to processing MRI data. CNN shows higher accuracy than SVM, ranging from 85% to 99%, while SVM only achieves accuracy between 83.33% and 97%. Then, Fig. 5 also indicates that processing with CNN is higher than SVM in X-ray data. This result is consistent with that obtained in MRI and CT-scan data. In this X-ray data, CNN achieves accuracy between 90.68% and 99.5%, while SVM ranges from 94.5% to 99.17%. A more detailed comparison is shown in Fig. 6.

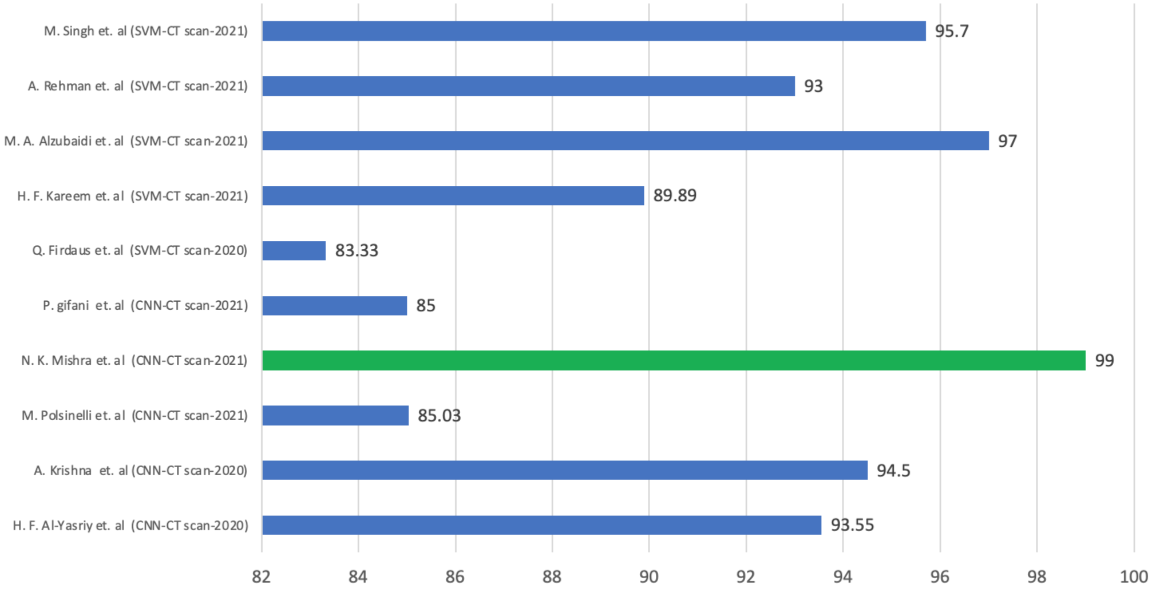

Fig. 4. Comparison of accuracy between previous studies on CT scan data using CNN and SVM methods

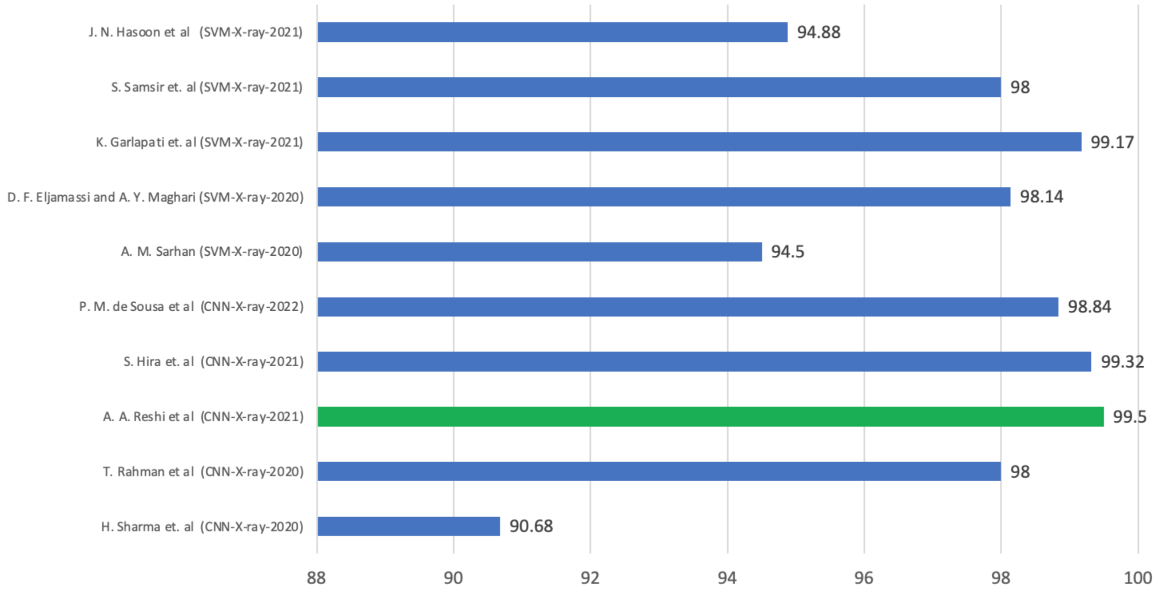

Fig. 5. Comparison of accuracy between previous studies on X-ray data using CNN and SVM methods

Fig. 6 shows that the accuracy results of CNN are better compared to SVM, both in processing MRI, CT scan, and X-ray data. SVM excels by obtaining maximum values of 99.74% for MRI, 99% for CT scan, and 99.5% for X-ray. However, there is an interesting observation that SVM produces better average accuracy for CT scan data. The difference between the average accuracy of SVM and CNN in processing CT scan data is not significant, only 0.36%. Meanwhile, from a global perspective, the average accuracy of CNN for all types of medical data is still superior with a value of 95.58%. Whereas the average accuracy of SVM is at 94.72% (Fig. 7). The difference is also not considerable, only 0.86%. This makes the distinction not significantly significant, although overall the CNN algorithm still outperforms SVM.

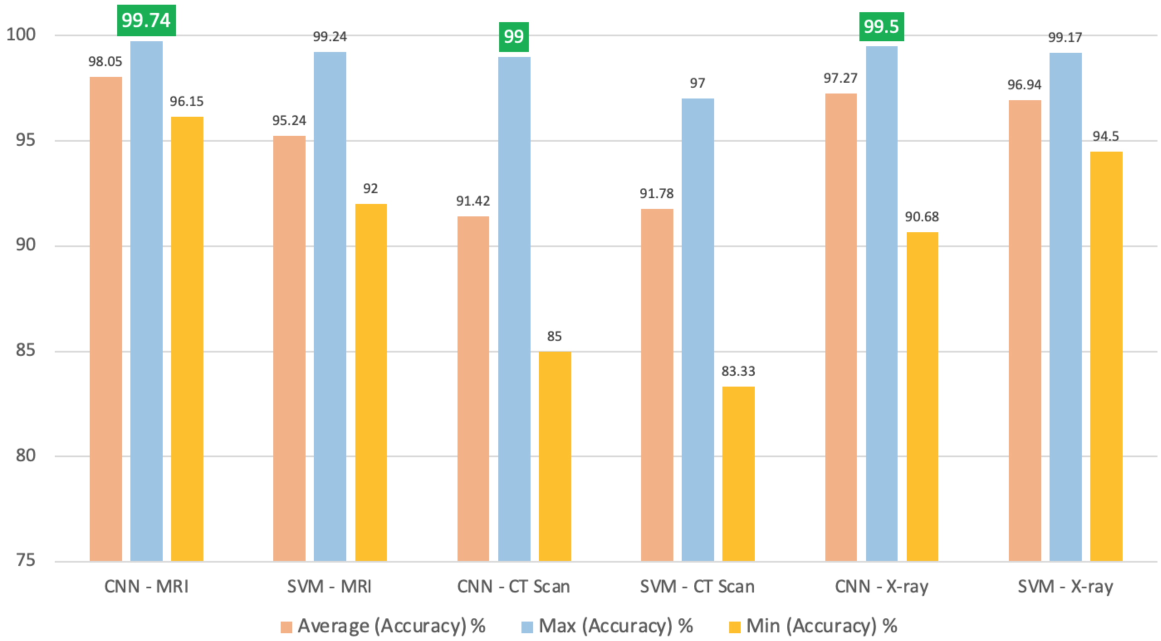

Fig. 6. Comparison of average accuracy, maximum accuracy, and minimum accuracy of CNN and SVM methods on medical data (MRI, CT scan, and X-ray) in previous studies

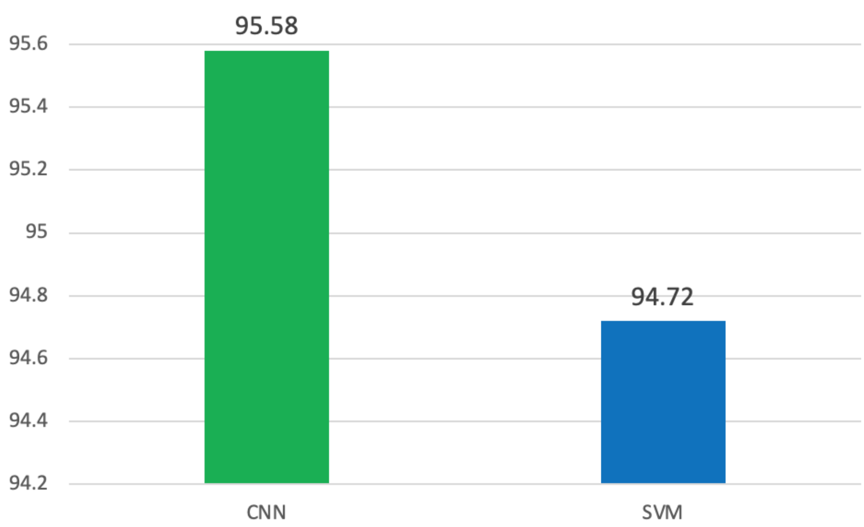

Fig. 7. Comparison of average accuracy between CNN and SVM for all referenced types of medical data

These findings indicate that CNN and SVM algorithms can provide excellent results in processing medical data. However, challenges in implementation will persist, including the need to address variations such as differences in image quality and variations in tumor size and shape. Additionally, interpreting detection results also requires supervision from medical experts to ensure that the detected tumors are indeed clinically relevant.

6. Advantages and Disadvantages of CNN and SVM

Based on the analysis provided, the CNN method has several significant advantages in processing medical data such as MRI, CT scans, and X-rays. First, CNNs can achieve very high classification results with accuracy reaching more than 90%, even approaching 100%, as seen in many studies summarized in Table 1. CNN's ability to automatically extract features from medical images enables it to effectively detect and classify various disease conditions with high accuracy. Furthermore, CNNs also exhibit considerable flexibility in handling medical data of various sizes and resolutions, as well as managing data with diverse levels of complexity.

Additionally, CNNs are capable of automatically learning from the provided data through the training process. This means CNNs can adapt to complex and varied data without requiring intensive manual tuning, making them easier to implement in various medical use cases. CNN's advantage also lies in its ability to process images at high speeds, making it suitable for medical applications where processing time is crucial, such as in early disease detection or rapid clinical decision-making.

Although CNNs have many advantages, there are also some drawbacks to consider. CNNs tend to require large amounts of training data to achieve high levels of accuracy. This can be challenging in cases where medical data availability is limited or difficult to obtain. Additionally, interpreting the results produced by CNNs may be challenging for individuals without a background in programming or AI, necessitating close collaboration between medical experts and data scientists to ensure reliable and meaningful results.

On the other hand, the SVM method has its own advantages. One of them is its ability to handle nonlinear classification problems well, despite SVM being essentially a linear algorithm. SVMs also tend to be more intuitively interpretable because of their basic concept involving the formation of a hyperplane to separate data classes. This makes SVM a good choice for cases where human interpretation of detection results is important, such as in clinical decision-making.

However, like CNNs, SVMs also have some disadvantages. One weakness is the need to adjust the right parameters, such as the C parameter and kernel function, which can significantly affect SVM performance. Additionally, SVMs tend to be less efficient in handling data with very high dimensions or a large number of features, as they require large storage and computation to calculate the optimal hyperplane. This can be a constraint in medical applications where medical data often have high dimensions and varying complexity.

7. Latest Developments in Related Studies

In recent developments in studies related to the use of CNN and SVM methods in medical data processing, new research continues to emerge with a focus on improving disease detection accuracy and enhancing algorithm performance. One recent trend is the development of more complex and sophisticated CNN and SVM models using techniques such as transfer learning [42] and ensemble learning [11], [83]. Although some of the selected case studies have already applied these [11], [70], [75], [80], [83], [91]. Recent studies also attempt to address challenges related to limited datasets in medical data processing. Some research has successfully utilized data augmentation techniques to increase variation in datasets, thereby assisting CNN and SVM models in learning better and producing better results [92], [93]. Additionally, some studies combine information from various types of medical images, such as MRI, CT scans, and X-rays, to improve disease detection accuracy.

In addition to advancements in data processing techniques, recent developments also focus on integrating AI technology with existing clinical systems. This includes the development of real-time systems to support diagnosis and clinical decision-making by medical professionals, especially the application of technologies like the Internet of Things (IoT) and concepts like Quality of Service (QoS) [94]-[96]. The use of CNN and SVM models in such clinical systems is expected to enhance efficiency and accuracy in disease diagnosis. Furthermore, in terms of security, the use of technologies such as cloud and blockchain could provide integrated and secure data solutions [97]-[101].

8. Conclusion

This research shows that CNN has a slightly higher average accuracy than SVM in processing medical data. CNN achieves an average accuracy of about 95.58%, while SVM's average accuracy is at 94.72%. Although the difference is relatively small, these numbers indicate that CNN tends to perform slightly better in some cases. However, both CNN and SVM obtain very good and reliable results in disease detection from medical images. For future research, it is recommended to further explore visualization techniques and feature interpretation to improve the interpretability of models, as well as to develop new approaches that are more adaptive to address variations in medical data.

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