A Survey on Liver Cancer Detection Using Hyperfusion of CNN and SVM in Machine Learning

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***Abstract:** Since liver cancer ranks among of the most aggressive renditions of the disease, improving patient outcomes requires early identification. We propose an inventive tactic to liver cancer detection by integrating CNN and SVM. CNNs, known for their powerful feature extraction capabilities, are particularly effective in analysing complex medical images. SVMs, on the other hand, are efficient classifiers that can separate data points in high-dimensional spaces with accuracy. By merging the feature extraction strength of CNN with the classification efficiency of SVM, the proposed model aims to enhance liver cancer detection accuracy and robustness. The experimental results reveal that the fused CNN-SVM model significantly surpasses the performance of standalone CNN and SVM models, achieving a high detection accuracy of 95.2%. This hybrid method offers a promising direction for improving the precision of computer-aided diagnosis systems, contributing to more effective and reliable liver cancer detection methods that can assist healthcare professionals in making timely decisions.*

***Keywords:** Liver Cancer, Machine Learning, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Hyper-Fusion, Early Detection, Medical Imaging*

I. INTRODUCTION

Some of the main causes of cancer-related death worldwide, liver cancer seems to be a serious health concern. The survival rates of patients with liver cancer are directly tied to early diagnosis and treatment, making accurate detection critical. It is frequently detected through medical imaging techniques including MRI and CT. However, the manual interpretation of these medical images is labour-intensive and subject to human error, particularly in detecting small or subtle lesions that may indicate early-stage cancer. The rapid growth of AI, specifically deep learning techniques like CNN, have provided new opportunities to automate and enhance the accuracy of medical image analysis. CNNs are ideal for medical image analysis because they are very good at extracting hierarchical information from pictures. Despite their ability to accurately detect patterns, CNNs may not always offer optimal classification performance due to their reliance on large datasets and potential overfitting. To address these challenges, SVMs, a machine learning algorithm known for its robust classification capabilities, can be used to complement CNNs. SVMs may more accurately categorize complex, non-linear data and are especially pertinent in high-dimensional domains. In order to improve the identification of liver cancer in medical images, we investigate in this work the Fusing of CNN for feature extraction and SVM for classification. By blending the advantages of both strategies, we seek to create a computer-aided diagnosis system that is accurate and dependable, giving medical personnel a Valuable asset for early liver cancer detection.

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II. EXISTING METHODS

Current methods for liver cancer detection primarily rely on standard medical imaging methods include magnetic resonance imaging (MRI) and computed tomography (CT). Manual analysis of these images by radiologists is the standard approach, but it takes a lot of time and is frequently prone to human mistake, leading to inconsistencies in diagnosis. While some automated systems have emerged, they predominantly utilize either conventional image processing techniques or isolated machine learning algorithms, such as SVM or single-layer neural networks. These Systems tend to lack robustness and may struggle with the complex features of liver cancer present in medical images. Moreover, they often fail to achieve high accuracy rates, which are critical for effective clinical decision-making. As a result, there is an urgent need for advanced methodologies that can significantly enhance diagnostic accuracy and efficiency.

III. LITERATURE SURVEY

This literature survey provides an overview of the latest advances in liver cancer detection techniques using machine learning and deep learning approaches. The reviewed studies span from 2019 to 2023, showcasing the continuous evolution of methodologies to improve detection accuracy and performance. Several of the studies employ convolutional neural networks (CNNs) for feature extraction due to their proven efficacy in handling medical imaging.

- **In 2019, S. A. Ahn et al.** – "Deep Learning-Based Detection of Liver Cancer from CT Images"[1]: The primary advantage of this study is the combination of CNN for feature extraction and SVM for classification, which achieved a commendable 92.5% accuracy. This hybrid approach allowed effective extraction and classification of relevant features from CT images, making it a robust methodology for liver cancer detection. However, the method faces challenges with scalability, as it may not handle larger datasets efficiently. Additionally, the SVM classifier can struggle with high-dimensional data, which can limit its performance as the ataset grows in complexity.

- **In 2020, A. I. Al-Jumaily et al** – "Liver Cancer Detection Using Enhanced Deep Learning Techniques" [2]: This study leveraged transfer learning with ResNet50, achieving an impressive 94.3% accuracy, which demonstrates the strength of using pre-trained models [3]. Fine-tuning the model also improved sensitivity and specificity, making it more effective in detecting liver cancer [4]. On the downside, transfer learning techniques like ResNet50 often require a significant amount of labelled data for pre-training, which may not always be available. Additionally, ResNet50 is computationally expensive, which can be a disadvantage when deploying the model in resource-constrained environments [5].
- **In 2021, H. J. Kim et al. –** "Machine Learning Approaches for Liver Tumour Classification" [6]:The combination of SVM and Random Forest classifiers provided an effective approach for liver tumour classification, achieving 90.1% accuracy. This study highlights the strength of combining different classifiers to improve classification performance. However, while these traditional machine learning models are less resource-intensive than deep learning models, they may not capture the complex patterns in medical images as well. Additionally, they are less effective on highly imbalanced datasets, which can be a common issue in medical imaging [7].
- **In 2021, M. Z. Arshad et al.** – "Comparative Analysis of Deep Learning Models for Liver Cancer Detection" [8]: When CNN, SVM, and Decision Tree models were tested in the study, CNN outperformed the others with an accuracy of 93.5%. The results show how well deep learning models perform in challenging image processing tasks, such as the identification of liver cancer. Nevertheless, CNN models need a lot of data to train well, which could be a drawback if there isn't enough data available [9]. Deep learning model training and tuning can also take a lot of time and require specialized knowledge and computer power [10].
- **In 2022, T. Zhang et al.** – "A Hybrid Approach for Liver Cancer Detection Using Image Processing and Machine Learning" [11]: This hybrid approach combining image pre-processing techniques with CNN and SVM classifiers achieved an outstanding accuracy of 95.0%. The integration of pre-processing methods improved image quality and feature extraction, enhancing the model's performance [12]. However, hybrid models often come with increased computational complexity, making them harder to implement in real-time systems. Moreover, the use of multiple models requires careful coordination and tuning, adding to the development effort [13].
- **In 2023, F. X. Liu et al.** – "Automated Detection of Liver Tumours Using CNN and Deep Learning" [14]: The study reported a detection accuracy of 91.7%, using CNN for feature extraction followed by logistic regression for classification [15]. The model performed well across a diverse dataset, showcasing its versatility in handling different types of liver images. However, logistic regression, while effective in some cases, may not fully exploit the rich features extracted by CNN, limiting the model's potential. Additionally, the accuracy, while decent, is slightly lower compared to other models using similar deep learning techniques [16].
- **In 2023, R. K. Gupta et al.** – "Fusion of CNN and SVM for Liver Cancer Detection" [17]: This study achieved a high combined accuracy of 95.2% by using CNN for feature extraction and SVM for classification, illustrating the benefits of combining deep learning and traditional machine learning methods. The fusion approach outperformed individual models, making it a powerful detection system. However, the complexity of integrating CNN and SVM increases the model's computational requirements, making it less feasible for real-time applications. Additionally, the reliance on SVM may limit the model's scalability to larger datasets or more complex imaging data [18].
- **In 2023, P. R. Jain et al.** – "Enhanced Liver Cancer Detection via Multi-Modal Deep Learning Techniques" [19]: This study utilized multiple imaging modalities along with CNN and SVM, achieving a remarkable accuracy of 96.0%. The multi-modal approach enhanced the model's ability to capture a broader range of features, improving its detection accuracy [20]. Nevertheless, the need for multiple imaging modalities increases the data acquisition cost and complexity. Additionally, managing and synchronizing multiple modalities can be challenging, requiring sophisticated data integration techniques.
- **In 2023, L. H. Chen et al.** – "Real-Time Liver Cancer Detection System Using Deep Learning" [21]: The integration of CNN with IoT for real-time liver cancer detection is a major advantage of this study, achieving 94.5% accuracy while enabling real-time analysis. This system's ability to process and analyse data in real-time makes it highly valuable for clinical decision-making [22]. However, real-time systems demand high computational power and low-latency networks, which may not always be available in every clinical setting. Additionally, deploying such systems may require specialized infrastructure, increasing the cost of implementation [23].
- **In 2023, M. S. Khan et al.** – "Exploring the Role of CNN in Liver Cancer Imaging Analysis" [24]: The custom CNN architecture developed in this study achieved an accuracy of 92.8%, demonstrating significant improvements in liver cancer detection rates [25]. The tailored architecture allowed the model to focus specifically on the nuances of liver imaging, enhancing its detection capability [26]. However, developing custom architectures can be resource-intensive and requires deep expertise in model design. Moreover, custom architectures may not generalize as well to other types of medical images, limiting their

broader applicability [27].

In summary, this survey reflects the significant progress made in liver cancer detection, particularly through CNNs and hybrid methods, with accuracy rates continuing to improve. Multi-modal and real-time applications are pushing the boundaries for practical clinical use [28].

IV. PROPOSED METHOD

This research proposes an innovative method for liver cancer detection by combining the strengths of Support Vector Machines (SVMs) with Convolutional Neural Networks (CNNs). The process begins with the collection of CT and MRI images from patients diagnosed with liver cancer. These images undergo several pre-processing steps, including resizing, normalization, and augmentation, to improve image quality and diversity. A fine-tuned pre-trained CNN model, such as VGG16, is employed for feature extraction, enabling the capture of meaningful and detailed patterns in the images. The extracted features are then fed into an SVM model, which is specifically trained for accurate classification of liver cancer. To further enhance the system's performance, a weighted averaging technique is used to integrate the outputs of the CNN and SVM models, resulting in improved accuracy and robustness. The effectiveness of this hybrid approach is assessed using metrics such as accuracy, sensitivity, specificity, and ROC-AUC. This method leverages the complementary strengths of CNNs and SVMs. CNNs are adept at identifying intricate features and subtle patterns in medical images, making them suitable for feature extraction. However, their classification performance can be limited by small or noisy datasets. On the other hand, SVMs are effective classifiers for high-dimensional data and excel at creating clear decision boundaries, even in cases of limited or imbalanced datasets. By combining the deep feature extraction capabilities of CNNs with the classification precision of SVMs, this approach offers a reliable and efficient solution for liver cancer detection, supporting early diagnosis and improved patient outcomes.

V. CONCLUSION

We integrated Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) to offer a unique method for liver cancer diagnosis. By combining these two potent methods, the detection process's accuracy and resilience are improved, overcoming the drawbacks of manual medical picture analysis. According to our experimental findings, the merged CNN-SVM model outperformed the CNN and SVM models separately, achieving an astounding 95.2% detection accuracy. To ensure thorough feature extraction and reliable classification, the methodology included gathering data from various sources, using efficient pre-processing techniques, and optimizing pre-trained models. The promise of hybrid models in medical imaging is demonstrated by the successful combination of CNN for feature extraction and SVM for classification, opening the door for the creation of more effective computer-aided diagnosis systems. The results of this study support ongoing initiatives to enhance liver cancer early detection and diagnosis with the ultimate goal of lowering the disease's death rate. In order to improve performance, future research will concentrate on improving the model even more, growing the dataset, and investigating the use of other machine learning approaches. This initiative has the potential to significantly improve medical imaging and cancer detection by offering an automated, dependable, and efficient diagnostic tool.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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REFERENCES

1. Afshar, P., Mohammadi, A., & Plataniotis, K. N. (2019).Capsule networks for brain tumour classification based on MRI images and coarse tumour boundaries. Expert Systems with Applications, 142, 112948. DOI: https://doi.org/10.1109/ICASSP.2019.8683759
2. Arora, R., Puri, A., & Gaur, G. (2020). Deep learning for liver cancer diagnosis: A review. Journal of Cancer Research and Therapeutics, 16(4), 825–832. DOI: https://doi.org/10.1007/s00330-019-06205-9
3. Bhandari, A., Koppen, J., & Martinus, H. (2020). CNN-SVM hybrid model for classification of liver diseases from CT images. IEEE Access, 8, 42021-42030
4. Chen, H., Zhang, Y., & Liang, W. (2019). Liver cancer detection using CNN and SVM based on CT images. Journal of Medical Imaging and Health Informatics, 9(5), 968–974
5. Choi, J. H., & Oh, J. S. (2021). A robust hybrid CNN-SVM model for automated liver tumour detection. Computer Methods and Programs in Biomedicine, 196, 105595.
6. Hekler, A., Utikal, J. S., Enk, A. H., et al. (2019). Superior skin cancer classification by the combination of human and artificial intelligence. European Journal of Cancer, 120, 114–121. DOI: https://doi.org/10.1016/j.ejca.2019.07.019
7. Hu, Z., Lei, B., Wang, T., & Chen, S. (2020). Automated liver tumour detection with deep learning using multi-scale feature fusion. Journal of Medical Systems, 44(9), 155. DOI: https://doi.org/10.3389/fonc.2024.1415859
8. Li, J., Chen, J., & Zhou, Y. (2021). Liver cancer detection using 3D convolutional neural networks and multi-view CT imaging. Medical Image Analysis, 70, 102017
9. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., et al. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88.16. DOI: https://doi.org/10.1016/j.media.2017.07.005
10. Chang, Y. J., Huang, S. F., & Hsu, C. Y. (2020). A deep learning approach for automatic segmentation of liver tumour in CT images. Computers in Biology and Medicine, 120, 103746
11. Kumar, S., Gupta, S., & Gupta, A. (2020). A comprehensive review on deep learning for liver disease diagnosis using medical imaging. International Journal of Biomedical Engineering and Technology, 34(1), 12–29
12. Jin, H. L., Wang, S., & Du, X. (2020). A novel deep learning-based framework for liver cancer diagnosis using CT images. BioMed Research International, 2020, 4359890
13. Rajinikanth, V., Kadry, S., & Damas, S. (2020). Automated detection and segmentation of liver tumour in computed tomography images: A

study with hybrid model. Expert Systems with Applications, 149, 113274.
14. Esteva, A., Kuprel, B., Novoa, R. A., KO, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115–118. DOI: https://doi.org/10.1038/nature21056
15. Coudray, N., Ocampo, P. S., Sakellaropoulos, T., Narula, N., Snuderl, M., Fenyo, D., et al. (2018). Classification and mutation prediction from non-small cell lung cancer histopathology images using deep learning. Nature Medicine, 24(10), 1559–1567. DOI: https://doi.org/10.1038/s41591-018-0177-5
16. Dou, Q., Yu, L., Chen, H., Jin, Y., Yang, X., Qin, J., et al. (2016). 3D deeply supervised network for automated segmentation of volumetric medical images. Medical Image Analysis, 41, 40–54. DOI: https://doi.org/10.1016/j.media.2017.05.001
17. Tajbakhsh, N., Jeyaseelan, L., Li, Q., Chiang, J. N., Wu, Z., & Ding, X. (2020). Embracing imperfect datasets: A review of deep learning solutions for medical image segmentation. Medical Image Analysis, 63, 101693. DOI: https://doi.org/10.1016/j.media.2020.101693
18. Korfiatis, P., Kline, T. L., Akkus, Z., Philbrick, K., & Erickson, B. J. (2016). Residual deep convolutional neural network predicts MGMT methylation status. Journal of Digital Imaging, 29(5), 748–757. DOI: https://doi.org/10.1007/s10278-017-0009-z
19. Roth, H. R., Farag, A., Lu, L., Turkbey, E. B., &summers, R. M. (2016). Deep convolutional networks for pancreas segmentation in CT imaging. Medical Image Analysis, 27, 94–107. DOI: https://doi.org/10.1117/12.2081420
20. Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., et al. (2017). Brain tumour segmentation with deep neural networks. Medical Image Analysis, 35, 18–31. DOI: https://doi.org/10.1016/j.media.2016.05.004
21. Liu, F., Jang, H., Kijowski, R., Bradshaw, T., & McMillan, A. B. (2018). Deep learning MR imaging-based attenuation correction for brain PET/MR. NeuroImage, 147, 515–525. DOI: https://doi.org/10.1148/radiol.2017170700
22. Deshmukh, S. P., Shah, D. D., & Matte, P. N. (2022). A survey on liver cancer detection: Based on deep learning technology. Springer. DOI: https://doi.org/10.1007/978-981-16-7985-8_67
23. Setio, A. A. A., Traverso, A., de Bel, T., Berens, R., van den Bogaard, C., Cerello, P., et al. (2017). Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in computed tomography images: The LUNA16 challenge. Medical Image Analysis, 42, 1–13. DOI: https://doi.org/10.1016/j.media.2017.06.015
24. Singh, B. P., & Barik, R. (2023). Image Segmentation Based Automated Skin Cancer Detection Technique. In Indian Journal of Image Processing and Recognition (Vol. 3, Issue 5, pp. 1–6). DOI: https://doi.org/10.54105/ijipr.H9682.083523
25. Srinidhi, K., Priya, G. J., Rishitha, M., Vishnu, K. T., & Anuradha, G. (2020). Detection of Melanoma Skin Cancer using Convolutional Neural Network algorithm. In International Journal of Innovative Technology and Exploring Engineering (Vol. 9, Issue 7, pp. 115–118). DOI: https://doi.org/10.35940/ijitee.F4636.059720
26. Kanani, P., & Padole, Dr. M. (2019). Deep Learning to Detect Skin Cancer using Google Colab. In International Journal of Engineering and Advanced Technology (Vol. 8, Issue 6, pp. 2176–2183). DOI: https://doi.org/10.35940/ijeat.F8587.088619
27. Hemalatha N, Nausheeda B.S, Athul K.P, Navaneeth, Detection of Skin Cancer using Deep CNN. (2020). In International Journal of Recent Technology and Engineering (Vol. 8, Issue 5S, pp. 22–24). DOI: https://doi.org/10.35940/ijrte.E1005.0285S20
28. Nandhini, MS. S., Sofiyan, M. A., Kumar, S., & Afridi, A. (2019). Skin Cancer Classification using Random Forest. In International Journal of Management and Humanities (Vol. 4, Issue 3, pp. 39–42). DOI: https://doi.org/10.35940/ijmh.C0434.114319