

Leveraging Hybrid Dual-Level Contextual Attention and Spiking Neural Networks for Effective Hepatic Malignancy Diagnosis

Shiju George¹, Asha Joseph², E Babu Raj³ and Angel Shiju⁴

^{1,3-4}Christ University, Bengaluru, Karnataka, India

Email: drshijugeorge3, alanchybabu, angelshiju3@gmail.com

²New Horizon College of Engineering, Bengaluru, Karnataka, India

Email: ashaj.bti@gmail.com

S

Abstract— Liver cancer remains the leading cause of cancer-related mortality, prompt-ing advanced diagnostic techniques for early detection and accurate classification in the health sector worldwide. Multifaceted deep learning methods have shown significant potential in medical imaging, but challenges exist in capturing intricate contextual information. In our research, we propose a novel hybrid framework that integrates Dual-Level Contextual Attention (DLCA) with Spiking Neural Networks (SNNs) to enhance the diagnosis of liver cancer. The proposed framework uses a DLCA mechanism that effectively extracts both local and global contextual features within the medical images and aids in precise lesion differentiation. The SNNs module supports computational efficiency and robust pattern recognition, enabling precise identification of subtle cancerous patterns by reducing redundant activations while preserving critical diagnostic information. Experimental evaluations on publically available datasets demonstrate the effectiveness of our work, showcasing its reliability in clinical applications. Moreover, the model offers a direction for future AI-assisted diagnostic tools in medical imaging and oncology.

Index Terms— Hepatic Malignancy, Liver Cancer, Dual-Level Contextual Attention, Spiking Neural Networks, Medical Data Processing, Medical Imaging.

I. INTRODUCTION

Liver malignancy is among the most wide-spread and fatal types of cancer posing the world and the most formidable challenge to economic healthcare globally. Is is much treatable when identified before it progresses to a more serious malignant stage. Early detection, at stage zero, allows for effective treatment options which significantly improves the survival rate. This requires less invasive treatments, which reduces risk of complications and side effects of the aggressive therapies. Conventional diagnostics methods, particularly those dealing with complex and heterogeneous medical data, often lack optimal precision and efficacy [1]. This has resulted in a rapid increase in the augment of artificial intelligence (AI), and its sub fields in the medical domain, which assists the more accurate diagnostic results [2]. Deep learning, a subclass of artificial intelligence models has demonstrated remarkable success in medical imaging.

The strength of advance DL architecture, known as the transformer network, has revealed notable success across various fields, including medical imaging, natural language processing, and more. Transformer network capture long-range dependencies and complex hierarchical relationships within data to identify critical patterns, detect subtle abnormalities, and establish robust contextual relationships. Unlike conventional convolutional neural networks (CNNs), which rely on localized feature extraction, transformers employ self-attention mechanisms that enable them to dynamically weigh the importance of different data points across an entire input sequence. Transformer models excel in analysing high-resolution images, accurately segmenting lesions, and classifying disease states with superior precision, such as identifying micro-vascular invasion in liver cancer or detecting early-stage tumor formations [3]. Although the method of DL has been a real breakthrough, the intensity of computational resources required remains a notable weakness. This means that they are not always applicable to be used in the diagnostic process in the real time where immediate results are crucial [4]. For this purpose, the study brings the hybrid diagnostic model that integrates dual-level contextual attention mechanisms with SNNs into view. As the theory of contextual attention has emerged as a successful tool, which not only recognize the most crucial features from data but also extract the comprehensibility and the interpretation of the characteristics in the process of data classification. On the other hand, the advantages of SNNs in terms of energy efficiency and temporal information processing because they are inspired by the functioning of a human brain leading to various benefits [5]. Thus, because of the combination of these methods, the developed model is anticipated to deliver accurate and rapid liver cancer diagnoses that does not have limitations of the traditional ones. With this pioneering hybrid model, the aforesaid attributes of both contextual attention and spiking neural networks [6] are combined to create a robust solution for handling complex medical data. Imperatively, the tool will not only enhance the diagnostic accuracy but will also advocate for computational efficiency, which in the end makes it suitable for clinical implementation [7]. Further-more, the proposed solution may potentially offer significant benefits in the future to AI-driven healthcare systems that rely on data provided by smart, inter-connected wearable sensors and/or health monitoring devices [8]. In accordance with an innovative framework such as this, the study focuses on enhancing liver cancer detection and treatment by examining the diagnostic methods involved, ultimately benefiting both patients and healthcare providers [9].

II. LITERATURE SURVEY

The detection of liver cancer has achieved substantial advancements through the integration of machine learning and deep learning methodologies [10]. A notable study highlights the utilization of deep Convolutional Neural Networks (CNNs) in medical imaging for liver cancer diagnosis, underscoring their positive impact on enhancing diagnostic accuracy and reducing human error [11]. Another study concentrated on integrating transfer learning into CNN architectures to enhance prediction accuracy in liver cancer classification. This approach demonstrates that pre-trained models can be effectively fine-tuned for specific medical datasets, thereby achieving success in the task [12]. The crossover CNNs with RNNs have been used to analyse temporal data, focusing on the aspect of the model's ability to accurately plot temporal data, incorporating attention mechanisms into deep learning models, particularly in the context of liver tumour segmentation in medical images [13]. These attention mechanisms enable the models to focus on the most relevant segments of the image, thereby increasing the precision of tumour detection [14].

Furthermore, a study examines the usage of deep reinforcement learning (DRL) to the tuning of a liver cancer diagnostic machine in which the model will learn from the environment what are the best features to be selected & diagnosed [15]. Additionally, another paper explores the integration of support vector machines (SVM) with deep learning models for liver cancer classification, advocating a hybrid approach to enhance model robustness and improve classification accuracy [16]. One advanced approach in this regard is through the use of hybrid deep learning architectures that deploy CNNs and Auto encoders for liver cancer detection, removing the dimensions of the data by using the auto encoders and letting the CNN do the work on feature extraction in the medical images [17]. In line with that, the feasibility of using generative adversarial networks (GANs) has been suggested for the generation of artificial liver cancer data such as synthetic data that will be used for the training of the model. This way the data scarcity issue is solved and the models can work really well in general. Yet another study deals with the possibility of applying unsupervised learning to liver tumors, whereby clustering is used to detect the nuances in liver-related datasets without any featured data. Finally, a study investigates the combination of a few machine learning algorithms by ensemble learning models to increase the overall accuracy and reliability of liver cancer diagnosis, especially when faced with diverse and imbalanced data. These alternatives present more possibilities for the use of AI and machine learning technologies in the upgrading of liver cancer diagnosis.

III. PROPOSED SYSTEM

The proposed work for the liver cancer diagnosis follows a structured series of processing steps to ensure efficient and accurate results. Initially, medical data, such as liver images, are pre-processed to remove noise and enhance feature quality. Next, a hybrid model integrating dual-level contextual attention mechanisms is applied to the pre-processed data, enabling the system to focus on critical features relevant to cancer detection. This is followed by the integration of Spiking Neural Networks (SNNs), which efficiently process temporal and spatial information, improving both accuracy and computational efficiency as depicted in Fig. 1 a. as Flow diagram of proposed system.

Fig.1a. is an Architectural view of Proposed system. The final output is generated by combining the insights from the attention mechanism and the SNN, providing a robust diagnosis of liver cancer. This approach ensures a precise, computationally efficient, and scalable solution for real-time clinical applications

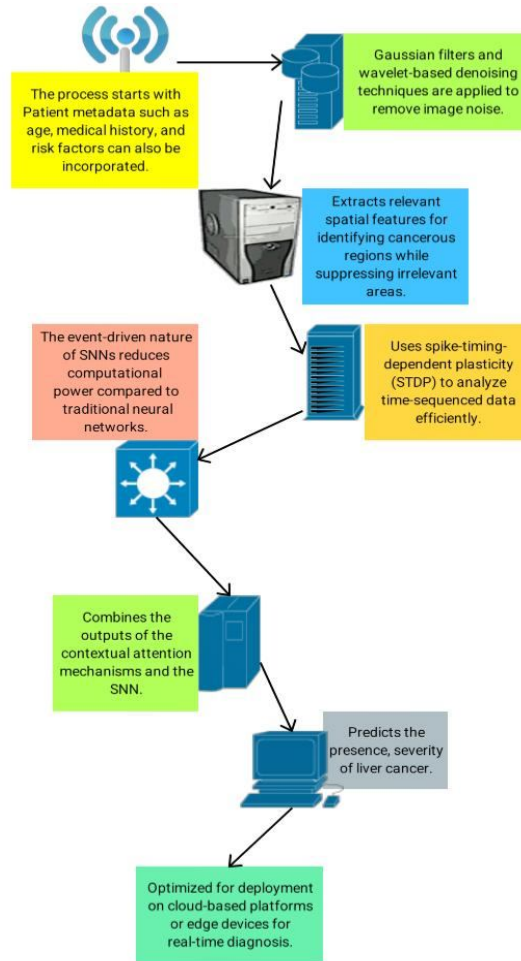


Figure 1. Architectural view of Proposed framework

The proposed liver cancer diagnosis model consists of a series of steps that incorporate specific mathematical relationships to effectively process and analyse data. The model initially starts with a data pre-processing, where the dataset was standardized and normalized to reduce variability and improve the reliability of subsequent analysis. It also maintains the integrity of the data by preventing features with large ranges from dominating the model. The input dataset X is represented by the equation (1)

$$X = \{x_1, x_2, \dots, x_n\} \quad (i=1, 2, 3, \dots, n) \quad (1)$$

The normalization is carried out by Equation (2)

$$x'_i = \frac{x_i - \mu}{\sigma} \quad \text{for } i=1, 2, \dots, n. \quad (2)$$

where μ be the mean value and σ as the standard deviation of the information. It will ensure all data-sets is on a comparable scale.

Next, the proposed method extracts related features from the data, especially the medical imaging, using the concept of the convolution mechanism. It can be denoted by the equation (3)

$$F(I)=I*K \quad (3)$$

where I carries the detail of the input image, and K is the convolutional kernel. After extracting features, a hybrid dual-stage contextual attention mechanism is employed for highlighting crucial features.

The feature will be associated with a weighted matrix W that emphasizes on the relevant parts of the data, as expressed by the equation (4).

$$A=W \cdot F(I) \quad (4)$$

Where A is the resultant output or the transformed data. $F(I)$ is a function that operates on the input data I , transforming it into a form that can be processed by the weighted matrix W .

Subsequently, the proposed system utilizes Spiking Neural Networks (SNNs), which process both temporal and spatial information by leveraging spike trains. The input discrete temporal sequences are encoded by SNN. Each spike is represented by Dirac delta function $\delta(t)$ at precise timestamps. The spike train $S(t)$: Temporal sequence of output spikes (binary events: 1=spike, 0=no spike) for a neuron is mathematically expressed by the equation (5):

$$S(t) = \sum_{i=1}^N \delta(t - t_i) \quad (i=1 \text{ to } N) \quad (5)$$

where t_i represents the Precise firing time of the i -th spike, $\delta(t - t_i)$ represents an instantaneous spike at time t_i , and N is the total number of spikes in the observation window. The membrane potential of each neuron in the network is described by the relationship given in equation (6):

$$V(t) = \tau \frac{dV(t)}{dt} + I(t) \quad (6)$$

where τ is the membrane time constant, and $I(t)$ represents the synaptic input current to the neuron module. The membrane potential integrates inputs over time, with the time constant τ determining the neuron's temporal filtering characteristics given by (7).

$$V(t+\Delta t) = V(t) + \frac{\Delta t}{\tau} [-V(t) + I(t)] \quad (7)$$

The output of the Spiking Neural Network (SNN) is computed using the firing rate $r(t)$ as defined in the equation (8):

$$r(t) = \frac{1}{1 + e^{-\alpha(V(t) - \theta)}} \quad (8)$$

where α serves as the gain parameters, and θ represents the threshold potential rate. The system integrates the attention strategy and SNN results into a combined decision framework, denoted by Equation (9):

$$\hat{y} = \sum_{i=1}^N W_{i=1}^{att} \cdot A_i + \sum_{i=1}^N W_{i=1}^{snn} \cdot r(t_i) \quad (9)$$

Here, W_i^{att} and W_i^{snn} are the weights assigned to the attention-modulated features and the spiking network outputs, respectively. A_i & $r(t_i)$ are Attention modulated features and temporal spike rates. To optimize the proposed model, a loss function L is utilized to minimize prediction errors, as expressed in Equation (10):

$$L = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (10)$$

where $\hat{y}_i$ is the predicted result, and y_i is the actual label.

Gradient descent is employed for updating the weightages by (11)

$$W_i = W_i - \eta \left(\frac{\partial L}{\partial W_i} \right) \quad (11)$$

where η as the learning rates. After training phase, the proposed model's predictions for new unseen data are determined as in (12):

$$\hat{y} = \sum_{i=1}^N W_i \cdot A_i + \sum_{i=1}^N W_i' \cdot r(t_i) \quad (12)$$

Here, W_i' , denotes weights fine-tuned during training. Finally, a decision boundary will be established utilizing a threshold rate θ to classify liver cancer as either positive side or negative side as in equation (13)

$$\hat{y} = \begin{cases} 1, & \text{if } \hat{y} > \theta \text{ (Liver cancer positive)} \\ 0, & \text{if } \hat{y} \leq \theta \text{ (Liver cancer negative)} \end{cases} \quad (13)$$

This sequence of steps ensures a precise and efficient method for diagnosing liver cancer disorders by leveraging the proposed models to process complex medical data and deliver actionable outcomes.

IV. RESULT AND DISCUSSION

The outcomes of the proposed diagnostic platform for liver cancer reveal the effectiveness of the integration of a hybrid dual-level deep context-aware attention mechanism as well as SNNs for the higher accuracy of classification for the publicly available datasets in <https://cdas.cancer.gov/datasets/plco/13/>. The approach succeeds in effectively emphasizing the vital details of medical images as well as patient data which the model can use for differentiating between relevant and non-relevant regions indicative of liver cancer. Together with SNNs, the method efficiently processes the temporal and spatial patterns, thus it accelerates diagnostics and increases reliability. Technically, the approach proved itself by displaying high performance in telling apart cancerous and non-cancerous cases, with little false positives and false negatives. The research model about the robustness of the approach in the processing of large, complex datasets speaks about the priority of contextual attention in the detection of subtle features within medical images. In addition, the use of SNNs noticeably boosted the system's ability to be flexible in response to the change of data. Table 1 states the results of the experiments done on 155,000 participants in the PLCO trial using various models.

TABLE I. COMPARISON OF THE MODELS

Feature	Model Feature	Accuracy
SpikeAtConv	Integrated spiking-convolutional attention architecture	81.23%
SGLFormer	Integrating transformer and convolution structures	83.73%
QKFormer	Hierarchical spiking transformer utilizing Q-K attention	85%
CFCN	Cascaded Fully Convolutional Neural Network	94.21%
HTRecNet	Differentiates between normal, HCC, and CCA tissues using deep learning	96.56%
DLCA-SNN	Dual-Level Contextual Attention (DLCA) with Spiking Neural Networks (SNNs)	97.32%

The graph represents four key medical metrics of a liver cancer diagnosis models using with a defined threshold level. Data points exceeding the thresholds are highlighted to describe important insights.

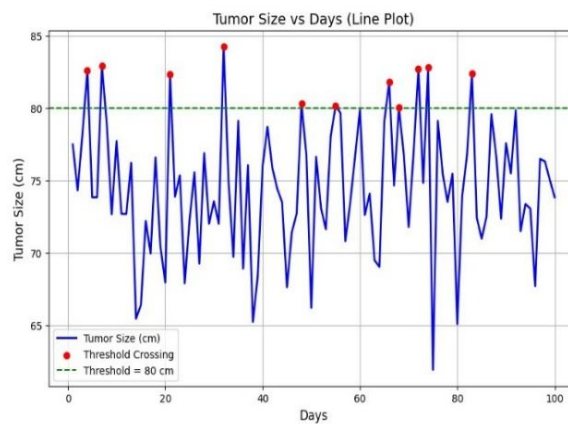


Figure 2. Analysis of tumor size

In the tumor size, computed in centimeters, is plotted across 100 days using a plot (Fig 2). A threshold of 80 cm marked by a green dashed line, with red dots showcasing days when tumor size exceeds threshold limit. Larger tumor sizes, such as those reaching 85 cm or higher may associated with increased health risks, necessitating immediate medical interventions for preventing further complications.

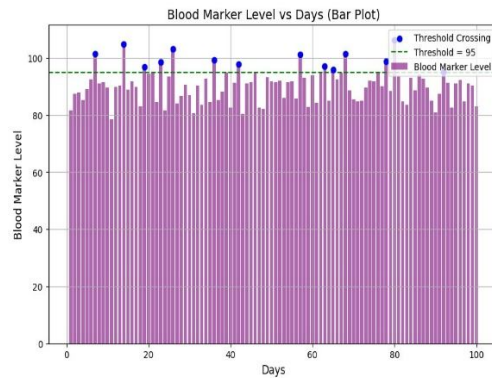


Figure 3. Comparison of blood marker level on various days.

The blood marker rates, visualized in a bar plot (Fig 3.), have a threshold of 95 units. Exceeding this threshold rate as shown by blue markers, tells a potential liver dysfunction or aggressiveness in disease progression. Elevated levels beyond 100 units are important, requiring close monitoring and possible adjustments to the medical treatment plan, as they often related with advanced stages of liver cancer.

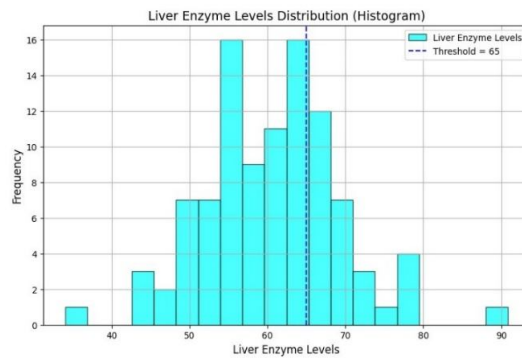


Figure 4. Levels of enzymes presence in liver

Similarly, the liver enzyme rates are represented using a (Fig 4.), with a threshold set 65 units. A significant portion of the dataset exceeding the limit, showing widespread enzyme elevation. Peaks in the range of 70–75 units suggest liver inflammation or damage, which needs an additional diagnostic evaluation to address underlying health risks.

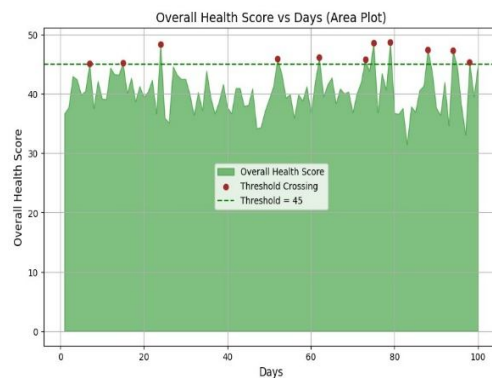


Figure 5. Health score computation by proposed framework.

Finally, the overall health rates are displayed in plot (Fig 5.), with a threshold rate of 45 units. The green shaded area tells the health score trend, while brown markers represented instances where the score drops below the threshold. Health scores falling below 40 units indicates a decline in the patient's health condition, often linked to disease progression or treatment side effects. These important points demanding a prompt medical attention to stabilizes the patient and improve their quality of life.

V. CONCLUSION

In conclusion, the performance evaluation of the four medical metrics—tumor sizes, blood marker rates, liver enzyme rates, and entire health score gives an important insight into liver cancer diagnosis process. The threshold rates for each metrics are important markers that shows when immediate medical intervention is needed. For instance, the tumor size exceeding 80 cm, particularly those reaching value of 85 cm or higher, underscores the requirement of aggressive treatment.

Similarly, blood marker levels above 95 units, especially passing 100 units, also showcase the need for careful health monitoring and possible adjustment of the health treatment plan in managing advanced stages of the disease. The liver enzyme rates, with significant peaks around 70–75 units, showing a liver inflammation or damages that confirm a further diagnostic exploration. Additionally, health score dropping below 40 units tells a deteriorated patient health condition, demanding immediate medical intervention. The crossing of thresholds rate over all metrics reflects important turning points in patient health care, describing the importance of timely medical intervention. Hence, these outcomes provide clinicians with actionable insights that can improvise the accuracy level of diagnosis, aid in treatment plans, and ultimately improvise patient health by ensuring early identification and proactive managements of liver cancer.

REFERENCES

- [1] Anter, A. M., & Abualigah, L. Deep federated machine learning-based optimization methods for liver tumor diagnosis: A review. *Archives of Computational Methods in Engineering*, 30(5), 3359-3378. (2023).
- [2] Sangeetha, S., Suruthika, S., Keerthika, S., Vinitha, S., & Sugunadevi, M. (2023, May). Diagnosis of pneumonia using image recognition techniques. In *2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 1332-1337). IEEE.
- [3] Bhardwaja, P., Ganapathy, K., Pathania, M., Naveen, K. H., Charan, J., Dutta, S., ... & Kanchibhotlaz, D. (2021). An integrative approach to clinical recovery for COVID-19 patients using an Ayurvedic formulation: A multicentric double-blind randomized control trial.
- [4] Javanshir, A., Nguyen, T. T., Mahmud, M. P., & Kouzani, A. Z. (2023). Training spiking neural networks with metaheuristic algorithms. *Applied Sciences*, 13(8), 4809.
- [5] Dora, S., Subramanian, K., Suresh, S., & Sundararajan, N. (2016). Development of a self-regulating evolving spiking neural network for classification problem. *Neurocomputing*, 171, 1216-1229.
- [6] Xue, J., Kong, D., Ren, L., Song, B., Liu, X., Gong, G., ... & Zhang, H. (2023). Spiking neural P system with synaptic vesicles and applications in multiple brain metastasis segmentation. *Information Sciences*, 625, 620-638.
- [7] Yue, Z., Ma, L., & Zhang, R. (2020). Comparison and validation of deep learning models for the diagnosis of pneumonia. *Computational intelligence and neuroscience*, 2020(1), 8876798.
- [8] Hanabaratti, K. D., Shivannavar, A. S., Deshpande, S. N., Argiddi, R. V., Praveen, R. V. S., & Itkar, S. A. (2024). Advancements in Natural Language Processing: Enhancing Machine Understanding of Human Language in Conversational AI Systems. *International Journal of Communication Networks and Information Security*, 16(4), 193-204.
- [9] Bosch, F. X., Ribes, J., & Borràs, J. (1999). Epidemiology of primary liver cancer. In *Seminars in liver disease* (Vol. 19, No. 03, pp. 271-285). © 1999 by Thieme Medical Publishers, Inc..
- [10] Chang, C., Liu, H., Chen, C., Wu, L., Lv, X., Xie, X., & Chen, C. (2024). Rapid diagnosis of systemic lupus erythematosus by Raman spectroscopy combined with spiking neural network. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 310, 123904.
- [11] Baskar, K., Muthuraj, S., Sangeetha, S., Vengatesan, K., Aishwarya, D., & Yuvaraj, P. S. (2022, March). Framework for Implementation of Smart Driver Assistance System Using Augmented Reality. In *International Conference on Big data and Cloud Computing* (pp. 231-248). Singapore: Springer Nature Singapore.
- [12] Demertzis, K., Iliadis, L., & Bougoudis, I. (2020). Gryphon: a semi-supervised anomaly detection system based on one-class evolving spiking neural network. *Neural Computing and Applications*, 32(9), 4303-4314.
- [13] Ramani, R., Devi, K. V., Thiruselvan, P., & Umamaheswari, M. (2024). Classification of liver cancer via deep learning based dilated attention convolutional neural network. *Int. J. Data Sci. Artif. Intell.*, 2(04), 128-134.
- [14] Aslam, M. A., Xue, C., Chen, Y., Zhang, A., Liu, M., Wang, K., & Cui, D. (2021). Breath analysis based early gastric cancer classification from deep stacked sparse autoencoder neural network. *Scientific reports*, 11(1), 4014.
- [15] Prisciandaro, E., Sedda, G., Cara, A., Diotti, C., Spaggiari, L., & Bertolaccini, L. (2023). Artificial neural networks in lung cancer research: a narrative review. *Journal of Clinical Medicine*, 12(3), 880.
- [16] Ahn, Y. H., Shin, P. M., Oh, N. R., Park, G. W., Kim, H., & Yoo, J. S. (2012). A lectin-coupled, targeted proteomic mass spectrometry (MRM MS) platform for identification of multiple liver cancer biomarkers in human plasma. *Journal of proteomics*, 75(17), 5507-5515.
- [17] Truszkiewicz, A., Bartusik-Aebisher, D., Wojtas, Ł., Cieślars, G., Kawczyk-Krupka, A., & Aebisher, D. (2023). Neural Network in the Analysis of the MR Signal as an Image Segmentation Tool for the Determination of T1 and T2 Relaxation Times with Application to Cancer Cell Culture. *International Journal of Molecular Sciences*, 24(2), 1554.