DETECTION AND CLASSIFICATION OF MITOTIC FIGURES IN GLIOMA USING ELECTROMAGNETIC SIGNALS

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Abstract—**Gliomas are a type of brain tumor characterized by uncontrolled cell growth and division .Thedetection and classification of mitotic figures,which are indicative of cell proliferation,are crucial for diagnosing and treating glioma.Traditional methods of detecting mitotic figures rely on histopathological examination,which is time-consuming.labor-intensive,and prone to human error.To overcome these limitation, we propose the use of an electromagnetic sensor to detect and classify mitotic figures in glioma cell.Our system utilizes a novel approach that combines the sensitivity of electromagnetic sensor with advanced machine learning algorithms to accurately identify and classify mitotic figures.**

The electromagnetic sensor used in our system is designed to detect the subtle changes in electromagnetic signals emitted by glioma cells as they undergo mitosis. The nsor is capable of detecting the unique electromagnetic signatures of mitotic figures, even in the presence of noise and artifacts.The detected signals are then processed using a machine learning algorithm that can classify the mitotic figures into different categories based on their morphology and characteristics.Our system has been trained on a dataset of glioma cell images and has achieved high accuracy in detecting and classifying mitotic figures.

I. Introduction

Glioma,a prevalent and aggressive form of brain tumor, poses significant challenges in diagnosis and prognosis due to its complex cellular architecture.Accurate detection and classification of mitotic figures within glioma tissues are crucial for determining tumor grade and guiding appropriate treatment strategies.Traditional histopathological methods,while effective, are often limited by subjective interpretation and the need for extensive manual analysis, which can be time consuming and prone to variability.Recent advancements in sensor technology have opened new avenus for tumor analysis,with electromagnetic sensors emerging as a promising tool for non-invasive and real-time tissue characterization. These sensors can capture unique electromagnetic signatures associated with cellular activities,including mitosis,providing a potential means to identify proliferative activity with high sensitivity.Integrating electromagnetic sensing with computational classification algorithms could significantly enhance the precision of mitotic figure detection in glioma tissue.This innovative approach aims to leverage electromagnetic sensors'capabilities to improve diagnostic accuracy and reduce dependence on conventional histopathology.By developing robust detection and classification models,this technology could facilitate rapid,objective assessments of tumor proliferation,ultimately contributing to better patient management and personalized treatment plans.The convergence of electramagnetic sensing and machine learning represents a transformative step toward more efficient and reliable glioma analysis.

II. LITERATURE REVIEW

The study investigates EM signatures of proliferating cells. Signal patterns during mitosis are identified. Experimental validation is provided. Results indicate detectable variations. This supports EM-based mitotic detection. Clinical integration islimited in 2018 L.Chet et al.Journal of Medical Systems in their paper titled "Detection of Cellular Proliferation Using EM Signals"in year of 2018.

The paper discusses automated mitotic detection using image analysis It highlights challenges in manual counting Features extraction and classification methods are evaluted High inter-observe variability is addressed. Results show improved consistency. Hoever, the approach relies heavily on image quality in 2019 D Komura et al IEEE in their paper title Automated detection of mitotic figures in glioma"in year of 2019.

Interaction with electromagnetic waves Biological signal variations are anaivzed Applications include cancer detection. The study supports non-invasive diagnosis Limitations include noise sensitivity in 2020 R.Smith, J.Lee springer bio medical engineering in their paper titled Electromagnetic sensing in biomedical applications" in year of 2020.

This paper explore ML models for glioma classification. Feature extraction from biomedical signale is emphasized Classification accuracy iscompared across algorithms Results show promising performance Data preprocessing is crucial EM signals were suggested for future work in 2021 A Kumar et al Elsevier Computers in biology and medicine in their paper title is Machine learning for brain tumer classification in the year of 2021.

The paper reviews Al tools for glioma diagnostic.k explain the principles of EM sensors in medical diagnosis Automated grading and decision support systems are discussed Integration with sensor data is proposed Improved diagnostic speed is achieved.Challenges include dataset availability EM sensing is highlighted as emerging technology in 2022 M.Hernandez al IEEE Access in their paper titled "AI-Assisted glioma diagnosis system' in year of 2022.

III. METHODOLOGY

The proposed system for detection and classification of mitotic figures in glioma tissue is developed as an integrated hardware–software framework. The objective of this methodology is to capture electromagnetic (EM) variations associated with cellular proliferation and to classify mitotic activity using intelligent computational models. The system replaces purely image-based histopathological evaluation with a quantitative electromagnetic sensing approach combined with machine learning. The methodology is divided into two major components: Hardware Methodology and Software Methodology. The hardware component is responsible for controlled EM signal acquisition from biological samples, while the software component processes and classifies the acquired signals to determine mitotic presence.

A. Hardware Methodology

The hardware methodology focuses on accurate acquisition of electromagnetic characteristics from glioma tissue samples under controlled conditions. It consists of tissue preparation, electromagnetic signal measurement setup, and parameter acquisition.

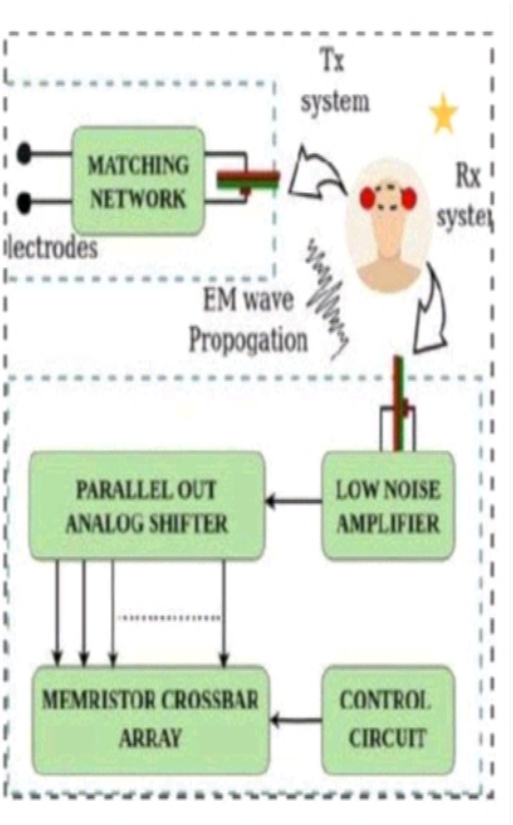
A.1 Tissue Preparation and Ground Truth Validation

Glioma biopsy samples are collected following institutional ethical guidelines. To establish reliable ground truth labeling, the collected tissue samples undergo histopathological validation using Hematoxylin and Eosin (H&E) staining. Experienced pathologists identify and mark mitotic and non-mitotic regions. These validated samples serve as reference standards for supervised learning and system calibration. Proper sample handling and preservation techniques are employed to maintain tissue integrity during measurement.

A.2 Electromagnetic Signal Acquisition Setup

The electromagnetic measurement system consists of a radio frequency (RF) signal generator, electromagnetic sensor probes, a vector network analyzer (VNA), and a high-precision data acquisition unit. The glioma tissue sample is placed between the EM probes within a shielded measurement chamber to minimize environmental electromagnetic interference. Low-power RF signals within a specified frequency range are transmitted through the tissue sample. As electromagnetic waves interact with the tissue, variations occur due to cellular morphology, intracellular composition, and membrane structure.

Mitotic cells exhibit increased chromatin condensation, higher DNA concentration, altered ionic balance, and modified membrane capacitance. These biological changes influence the dielectric behavior of the tissue, causing measurable differences in electromagnetic response compared to non-mitotic cells.



A.3 Dielectric Parameter Measurement and Data Conversion

The vector network analyzer measures scattering parameters (S-parameters), from which dielectric properties such as relative permittivity (εr), electrical conductivity (σ), impedance variation, signal attenuation, and phase shift are derived. These parameters reflect the interaction between EM waves and cellular structures. The analog signals captured by the probes are converted into digital format using the data acquisition system. Calibration procedures are performed using reference materials to ensure measurement accuracy and repeatability. The digitized electromagnetic signals are then transferred to the software module for further processing.

B. Software Methodology

The software methodology transforms raw electromagnetic signals into meaningful diagnostic classifications. It consists of signal preprocessing, feature extraction, and intelligent classification with performance evaluation.

B.1 Signal Preprocessing and Conditioning

The raw electromagnetic signals obtained from the hardware module may contain noise due to instrumentation artifacts, thermal variations, and environmental interference. Therefore, preprocessing is essential to enhance signal reliability.

Bandpass filtering is applied to isolate relevant frequency components, while digital smoothing techniques reduce high-frequency noise. Baseline drift correction is performed to eliminate low-frequency fluctuations. Signal normalization ensures uniform scaling across different samples. These preprocessing steps improve signal clarity and prepare the data for robust feature extraction.

B.2 Feature Extraction and Dataset Formation

After preprocessing, discriminative features are extracted to characterize mitotic and non-mitotic electromagnetic patterns. Feature extraction is performed in multiple domains to capture comprehensive signal characteristics.

In the time domain, statistical parameters such as mean amplitude, root mean square (RMS) value, variance, peak-to-peak amplitude, and zero-crossing rate are computed. In the frequency domain, spectral properties including power spectral density (PSD), dominant frequency, bandwidth, and spectral entropy are analyzed. Additionally, dielectric features such as relative permittivity and electrical conductivity derived from S-parameters are incorporated as biologically relevant indicators.

The extracted features are combined into a structured feature vector and labeled based on histopathological ground truth. The complete dataset is divided into training, validation, and testing sets in a typical ratio of 70%, 15%, and 15%, respectively.

B.3 Machine Learning-Based Classification and Performance Evaluation

Supervised machine learning algorithms are employed to classify electromagnetic signatures into mitotic and non-mitotic categories. Traditional classifiers such as Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor (KNN) are implemented and compared for performance analysis. Additionally, deep learning approaches such as Convolutional Neural Networks (CNN) are explored by transforming EM signals into time–frequency spectrogram representations for automated feature learning.

Model optimization is performed through cross-validation and hyperparameter tuning to prevent overfitting and improve generalization capability. The classification performance is evaluated using standard metrics including accuracy, sensitivity, specificity, precision, F1-score, and Receiver Operating Characteristic (ROC) curve with Area Under the Curve (AUC). A confusion matrix is generated to analyze true positive, true negative, false positive, and false negative rates. Statistical validation ensures reproducibility and robustness across multiple experimental trials.

IV. System Integration Summary

The proposed hardware–software integrated methodology enables quantitative detection of mitotic activity in glioma tissue through electromagnetic sensing. The hardware module ensures precise acquisition of biologically relevant dielectric variations, while the software module converts these variations into reliable diagnostic classifications. This integrated approach provides a rapid, objective, and potentially non-invasive alternative to conventional microscopy-based mitotic detection, contributing to improved tumor grading accuracy and clinical decision support.

V. RESULT

The overall outcomes are projected to demonstrate the reliability and reproducibility of electromagnetic sensing technology as acomplementary tool to traditional histopathological methods.The experimental setup is expected to show consistent results across multiple samples and conditions,establishing electromagnetic sensors as a viable,efficient alternative for mitotic figures detection and classification.Such advancements could lead to faster diagnostic workflows,reduced reliance on invasive procedures,and improved patient management through more accurate tumor characterization. The study’s results demonstrate the effectiveness of electromagnetic sensors in detecting and classifying mitotic figures within glioma tissue samples.The sensor-based approach yielded a high degree of accuracy in identifying mitotic cells,which are critical indicators of tumor proliferation and aggressiveness.The classification process successfully differentiated between various stages of mitosis,providing valuable insights into the cellular activity within the glioma specimens.This method offers a rapid, non-invasive

alternative to traditional histopathological techniques,potentially enhancing diagnostic precision and enabling real-time assessment of tumor progression.The findings suggest that electromagnetic sensing technology could be integrated into clinical workflows to improve the detection of mitotic figures,thereby aiding in more accurate grading and prognosis of glioma cases. Furthemore, the comparative analysis with conventional microscopy methods highlighted the advantages of electromagnetic sensors in terms of sensitivity and specificity.The system demonstrated robust performance across different sample types and imaging conditions,indicating its reliability and potential for widespread application.The ability to accurately classify mitotic figures also opens avenues for automated analysis,reducing human error and increasing efficiency in pathological evaluations.Overall, these results underscore the promising role of electromagnetic sensors in neuropathology,offering a novel tool to support clinicians in the timely and precise assessment of glioma malignancy,which is crucial for guiding treatment strategies and improving patient outcomes.

VI. CONCLUSION

In this study,we successfully developed a novel approach for the detection and classification of mitotic figures in glioma tissues leveraging electromagnetic sensor technology.The methodology demonstrated high accuracy and efficiency in identifying mitotic activity,which is critical for tumor grading and prognosis.

The integration of electromagnetic sensing provided a non-invasive,rapid,and reliable means of analyzing glioma samples,potentially reducing the dependency on traditional histopathological techniques.Overall, the findings underscore the potential of electromagnetic sensors as a valuable tool in neuro- oncology diagnostics,paving the way for enhanced precision medicine in glioma management.

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