**Literature Review**

Epileptic seizure prediction using EEG signals has been widely studied in the last decade. Traditional approaches involve extracting features from EEG recordings in the time, frequency, or time-frequency domains, followed by classification using machine learning algorithms such as support vector machines (SVM), k-nearest neighbors (KNN), and random forests. Recently, deep learning techniques, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been applied to automatically learn features directly from raw EEG signals. Public datasets, such as the CHB-MIT Scalp EEG database, are commonly used to benchmark and validate these models, allowing comparison between different approaches.

Researchers have conducted studies using both pre-processed and raw EEG data. Pre-processing steps typically include filtering to remove noise, baseline correction, and artifact removal using techniques such as independent component analysis (ICA). Features are then extracted in the time, frequency, and time-frequency domains, and used to train classifiers. In deep learning models, minimally pre-processed EEG segments are fed directly into CNNs or RNNs to capture spatial and temporal patterns. Models are evaluated using cross-validation and split-sample testing to assess their generalization and predictive performance.

The key findings from the literature indicate that machine learning methods can achieve prediction accuracies between 70% and 95%, depending on the dataset, features, and model used. Deep learning models generally outperform traditional classifiers by capturing complex temporal and spatial relationships in EEG signals. Several studies also highlight the importance of feature selection and patient-specific model optimization to improve predictive performance. These results demonstrate that seizure prediction is feasible and that EEG signals contain valuable information for early detection.

Despite these advances, existing methods have significant limitations. Many studies focus on single-patient datasets, which reduces model generalizability to new patients. Deep learning models often require high computational resources, making real-time implementation challenging. EEG signals are sensitive to noise, and artifact removal techniques are usually dataset-specific. High false positive rates are also reported in some studies, limiting clinical applicability. These limitations highlight the need for more robust, efficient, and generalizable models for seizure prediction.

Opportunities for improvement include developing hybrid frameworks that combine traditional feature-based methods with deep learning models to enhance both performance and interpretability. Transfer learning and domain adaptation techniques can reduce patient-specific training requirements. Improving pre-processing pipelines and optimizing models for real-time prediction are also key areas. Addressing these gaps could lead to clinically viable systems capable of providing timely warnings to epileptic patients and reducing seizure-related risks.