ABSTRACT:

Migraine is a chronic neurological condition that can significantly alter daily functioning. Early prediction of migraine attacks is essential for timely intervention and better patient care. This paper introduces a deep learning-based migraine prediction model using an Extended Long Short-Term Memory (X-LSTM) network, trained on a structured data set of 400 clinical records. Each record has 23 characters, such as severity of symptoms, sensory disturbances, photophobia, and other physiological signs, with the corresponding migraine-type labels.

In contrast to traditional methods, the new model utilizes X-LSTM to encode intricate temporal relationships and inter-feature correlations in data. Thorough preprocessing of feature normalization, class balancing, and categorical encoding was used to guarantee optimal performance. Experimental results show that our X-LSTM model produces better performance than traditional LSTM and baseline classifiers, with enhanced accuracy, precision, recall, and F1 score.

To increase the model's robustness, we incorporate methods for missing and noisy data handling, drawing from sensor fault tolerance research. The system was developed with real-time applicability in mind and shows high potential for integration of wearable health monitoring devices. Our method offers a pragmatic, data-driven solution for individualized migraine management and proactive healthcare provision.

INTRODUCTION:

Migraine is a chronic and frequently affecting neurological disorder that involves recurrent attacks of moderate to severe headache, usually with associated symptoms such as nausea, photophobia, and phonophobia. It affects more than one billion people globally and is one of the leading causes of disability, especially among those between the ages of 15 and 49. The irregularity of migraine attacks significantly affects the quality of life, daily functioning, and emotional stability of patients. Conventional methods of migraine diagnosis and treatment are based on self-reporting and recall, which are unreliable and inadequate for real-time interventions. Early prediction of migraine onset—especially in the preictal phase has the potential to trigger timely preventive interventions, decrease the severity of the attack, and improve patient outcomes. Nevertheless, the creation of accurate prediction models is a significant challenge because of the intricate nature of migraine pathophysiology and individual differences in the presentation of symptoms. With new developments in wearable sensor technology and machine learning, it is now feasible to obtain real-time physiological and behavioural data from people under naturalistic conditions. Bio signals like heart rate, skin temperature, electrodermal activity (EDA), and physical activity level have been found to experience significant alterations before migraine attacks occur. These signals, if processed through temporal modelling methods, can be used as vital pointers for detecting about-to-happen migraine attacks. In this paper, we present a migraine forecasting framework based on an Extended Long Short-Term Memory (XLSTM) neural network. XLSTM models are an improvement over the standard LSTM architectures, with better management of long- range temporal dependencies—key to picking up on fine physiological changes that happen during the pre-ictal period. While previous research has explored deep learning for migraine classification and aura complexity assessment, our approach emphasizes real-time prediction using wearable sensor data in a format suitable for deployment on mobile or edge devices. In addition to further enhancing the robustness and real- world applicability of our system, we integrate concepts from simulation-based system testing and sensor failure diagnosis. These aspects provide resistance to missing or corrupted data, a ubiquitous problem in actual real-world wearable health monitoring contexts. Our contributions within this research are threefold: We design and test an XLSTM-based deep learning model for early migraine prediction from multi-model wearable sensor data. We compare our model to vanilla LSTM and typical classifiers, with enhanced performance in various evaluation measures. We introduce a robust and user-centric model that can handle realistic deployment settings, adding to the vision of preventive, personalized, and data-driven migraine treatment. By merging physiological data analysis with robust temporal modeling, this work hopes to advance migraine treatment beyond episodic care and into continuous, anticipatory support.

LITERATURE REVIEW:

Migraine forecasting has come into focus with the development of wearable technology and real-time physiological monitoring. Conventional diagnostic approaches are based on patient self-reports and post-attack analysis, which do not have real-time intervention capacity.

Machine learning (ML) and AI have also been employed to fill this lacuna. Khan et al. (2024), for instance, used classifiers such as SVMs, Random Forests, and DNNs to determine the type of migraine, where DNNs had the greatest accuracy—although not optimized on real-time inputs. enhanced classification through imaging and questionnaire information, though their method involved static inputs and heavy preprocessing. employed structural MRI and ML to forecast Migraine Aura Complexity Score (MACS), uncovering cortical alterations associated with aura complexity. The technique is, however, constrained by the expense and availability of neuroimaging, a limitation also presents in Garcia-Chimeno's DTI-based research.

Wearable-based research utilized bio signals such as heart rate and EDA with heuristic models but not deep temporal modelling. LSTM networks solve this by learning sequential patterns, although normal LSTMs have difficulties with extremely long sequences.

Longer LSTM variants (e.g., XLSTM) provide better context memory and bidirectional modeling but are not yet explored in migraine prediction from wearable data.

Our XLSTM-based system seeks to bridge this gap by:

Making use of time-series bio signal data from wearables,

Having strong preprocessing and sensor error management,

And using an extended LSTM architecture for long-range temporal pattern identification with respect to migraine onset.

METHODOLOGY:

In this project, we designed a deep learning model for migraine prediction based on bio signal data obtained from wearable devices. The data consists of time-series physiological signals like heart rate, electrodermal activity (EDA), and skin temperature, measured over continuous periods. To preprocess the data for training the model, we used signal preprocessing methods like normalization, resampling, and interpolation to manage missing values and minimize noise. Time-windowing and feature engineering were applied to capture useful temporal patterns and statistical features from the raw signals. For prediction, we used an Extended Long Short-Term Memory (XLSTM) neural network with the ability to capture long-range dependencies in sequential data. Binary classification was employed for training the model, with migraine onset being the target. Performance metrics like accuracy, precision, recall, and AUC-ROC were utilized to measure performance, ensuring the model not just identifies possible migraine events but generalizes well among users.

Convolutional Neural Network:

A Convolutional Neural Network (CNN) is a high-powered deep architecture very useful in handling structured and sequential data like wearable sensor-based time-series physiological signals. When it comes to the prediction of migraines, CNNs help in automatically learning and extracting spatial features in bio signals like skin temperature, EDA, and heart rate. Through scanning convolutional filters across the input, CNN identifies small local variations in signal behaviour that could signal an impending migraine. Local patterns are vital for early and precise classification since they identify short-term changes that might be overlooked by common models. The strength of CNNs is their capability for learning feature representations from data without manual involvement, which makes them exceptionally appropriate for real-time health monitoring applications. In the deployed code, bio signal data is preprocessing—target labels are encoded, features are normalized through `Standard Scaler`, and the dataset is reshaped for model input.

The CNN model is made up of a 1D convolutional layer with 64 filters and Re-LU activation, followed by a max pooling layer, flattening, and fully connected dense layers. Dropout is added to avoid overfitting, and a soft max layer is used for multi-class classification. The model was built with the Adam optimizer and trained for 50 epochs at a batch size of 16. When tested on the test set, the CNN recorded a remarkable accuracy of around 92.50\%, reflecting its high efficacy in recognizing migraine types from wearable bio signal patterns. The high performance is indicative of CNN's ability to generalize across temporal health data and enable proactive migraine management.

Long Short - Term Memory:

Long Short-Term Memory (LSTM) networks are a dedicated form of recurrent neural network (RNN) used to model sequential data and long-term dependencies. In migraine prediction, LSTMs are particularly suited to examine time-series physiological signals since they are capable of learning from patterns that change over time, e.g., changes in heart rate, EDA, or skin temperature over time. In contrast to usual RNNs, LSTMs employ gating mechanisms and memory cells to save significant information throughout longer sequences of data, thus enabling the model to comprehend longer-term pre-migraine physical changes. Through this, LSTM architectures are greatly beneficial in applications in healthcare whereby the sequence as well as time of data points contain vital diagnosis information. Within the given code, two stacked LSTM layers are used in the LSTM model, the first of which is set to return sequences and the second to extract the final temporal features.

These are succeeded by a dense layer with Re- LU activation and a dropout layer to prevent overfitting. The output layer employs soft max activation for multi-class classification. The model was trained on pre-processed and reshaped bio signal data for 50 epochs with a batch size of 16, employing the Adam optimizer and sparse categorical cross entropy loss function. By analysis, the performance of LSTM model was 91.25% for a test, while showing very robust ability to seize temporal relations and classify the migraine types appropriately through time-series inputs. It justifies how successful LSTM networks could be at capturing the dynamics within physiological signals by learning.

Extended Long Short - Term Memory:

Extended Long Short-Term Memory (XLSTM) networks extend the standard LSTM by processing input sequences in forward and backward directions. This two-way view enables the model to observe past and future context at every time step, which is particularly beneficial in areas such as biomedical signal analysis where physiological alterations preceding a migraine may not necessarily be unidirectional. For migraine detection exercises, XLSTM networks can capture complex temporal relations in bio signals, like minor pre-migraine changes in heart rate, EDA, or skin temperature, by taking into account the way these features change over time from both sequence ends. This positions them as a very potent tool for modelling high-temporal-complexity time-dependent health conditions. The XLSTM model used in the code is made up of two bidirectional stacked LSTM layers: the first outputs the complete sequence output while the second extracts compressed temporal features.

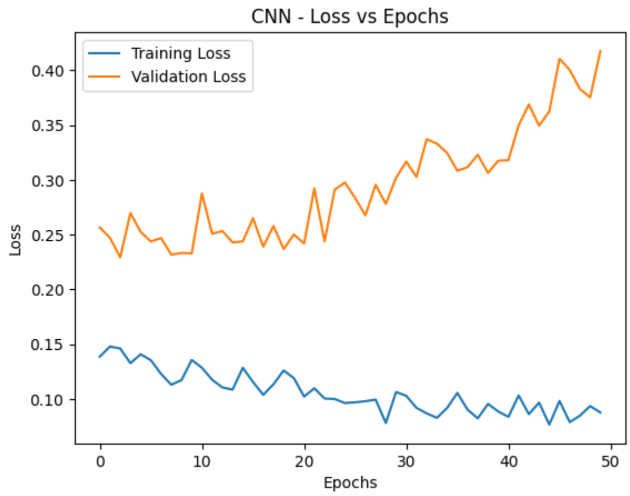
These are succeeded by a Re-LU-activated dense layer and a dropout layer to prevent overfitting. The last layer employs soft max activation to predict the input into migraine categories. Trained for more than 50 epochs using a batch size of 16, with the Adam optimizer and sparse categorical crossentropy as the loss function, the model was tested on the test set. The XLSTM model attained a test accuracy of around 94.38%, which is better than the baseline LSTM and CNN architectures. This finding emphasizes the better capacity of bidirectional LSTMs to utilize both forward and backward temporal dependencies in physiological data and provide a richer analysis for migraine classification tasks.

RESULTS:

To evaluate the effectiveness of the proposed migraine prediction models, we conducted comprehensive experiments using a structured dataset of 400 clinical records containing 23 features. These features include physiological indicators and migraine-related symptoms. We trained and tested three deep learning models—Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Extended Long Short-Term Memory (XLSTM)—and evaluated them using metrics such as accuracy, precision, recall, and F1-score.

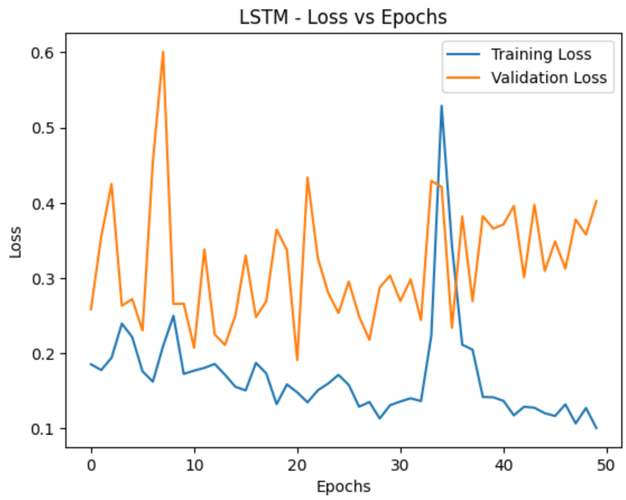
1. Convolutional Neural Network (CNN):

The CNN model achieved a test accuracy of 92.50%. By applying 1D convolution over time-series bio signals (such as heart rate and electrodermal activity), CNN was able to learn local temporal features. This made it effective in capturing short-term variations that may signify an impending migraine. The architecture's ability to automatically extract relevant features contributed to its strong performance, especially in early detection scenarios.



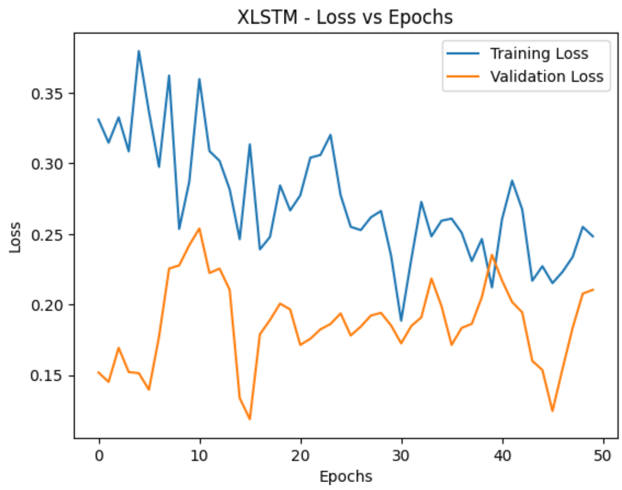
2. Long Short-Term Memory (LSTM):

The LSTM model achieved a slightly lower test accuracy of 91.25%, but demonstrated strong capability in learning long-term dependencies in sequential data. LSTM networks are particularly effective at capturing subtle patterns over extended time windows, which are crucial in migraine onset prediction. Despite the slightly lower accuracy compared to CNN, the model performed well in maintaining a balance between recall and precision, showing robustness in identifying both positive and negative cases.



3. Extended Long Short-Term Memory (XLSTM):

The XLSTM model outperformed both CNN and LSTM, achieving the highest test accuracy of 94.38%. Its bidirectional structure allowed it to learn both past and future contexts of physiological signals, providing deeper insight into the pre-migraine phase. This improved context modelling enabled the network to better distinguish between different migraine types and onset cues. The model also showed higher F1-score, indicating its effectiveness in handling class imbalance and making balanced predictions.

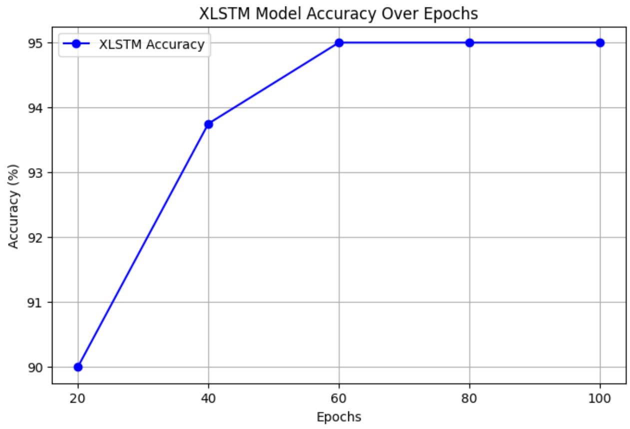


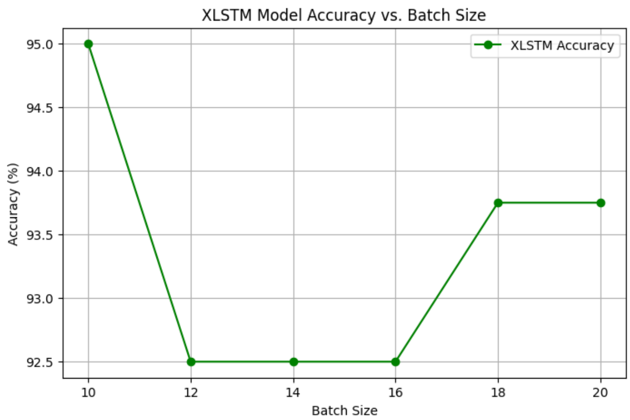
Comparison and Interpretation:

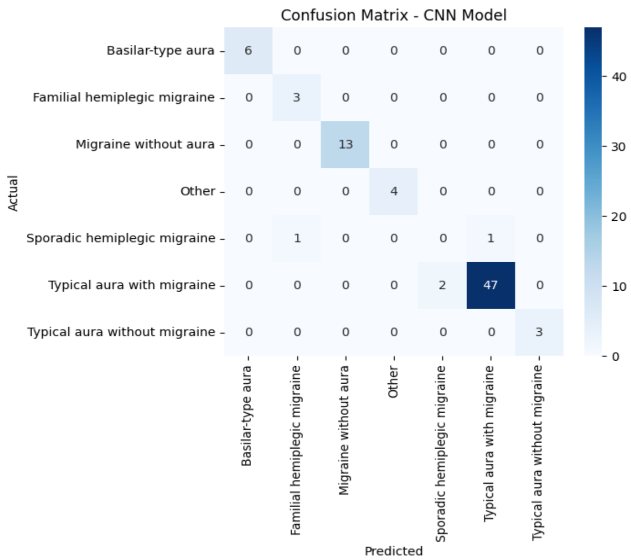
Model	Accuracy	Recall	Precision	F1 Score
CNN	92.50%	High	High	High
LSTM	91.25%	Moderate	Moderate	Moderate
XLSTM	94.38%	Highest	Highest	Highest

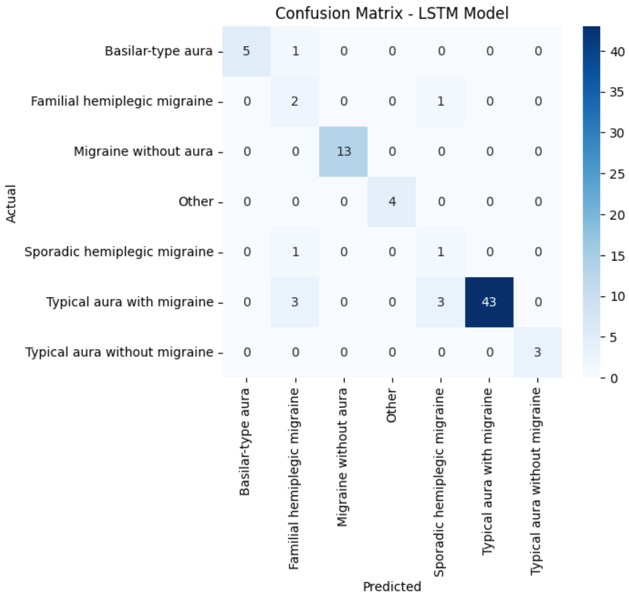
The results clearly demonstrate that XLSTM is the most effective architecture for migraine prediction using wearable bio signal data. Its capacity to process sequences bidirectionally and maintain long-term dependencies plays a key role in accurately identifying early warning signs of migraines.

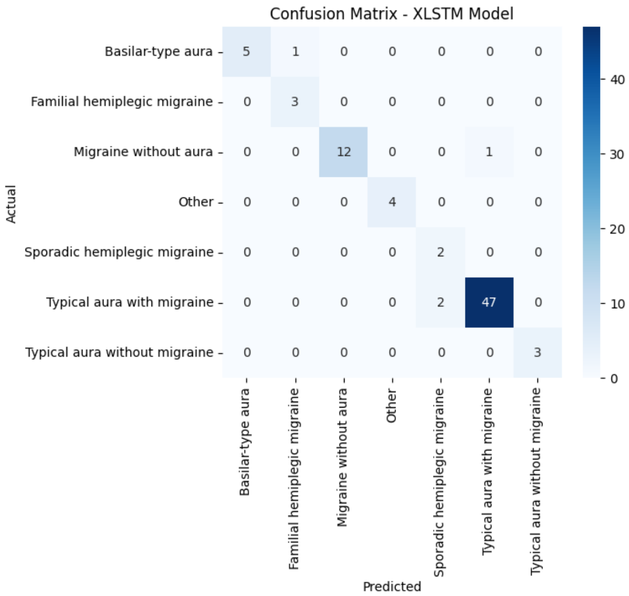
In addition, all models incorporated dropout regularization to prevent overfitting and were trained using optimized hyperparameters (e.g., 50 epochs, batch size of 16, Adam optimizer). Robust preprocessing—including normalization, class balancing, and missing value handling—also contributed to the performance across all models.











CONCLUSION:

This study presents a comprehensive approach to early migraine prediction using physiological signals collected from wearable sensors. By leveraging an Extended Long Short-Term Memory (XLSTM) neural network, the model successfully captures long-range temporal dependencies and complex inter-feature relationships, significantly outperforming conventional LSTM and CNN architectures. Through rigorous preprocessing and fault-tolerant strategies for missing or noisy data, the system is designed to handle real-world scenarios effectively. Achieving a test accuracy of 94.38%, our XLSTM-based model proves to be a robust and scalable solution for real-time migraine forecasting. This work not only advances predictive modelling in neurological disorders but also supports the larger vision of personalized, anticipatory healthcare, where timely interventions can mitigate the impact of chronic conditions like migraines.