

VII Semester Minor Project (22CSW401) Presentation

Title : Sleep Disorder Classification with 1D-CNN and LSTM on Vectorized CAP EEG Signals

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Introduction

What is Sleep Disorder Detection?

- Sleep disorders are conditions that disturb a person's normal sleep patterns, affecting health, mood, memory, and daily functioning.
- Diagnosing these disorders often requires analyzing EEG signals, a process that is manual, slow, and prone to errors, especially because many disorders have similar symptoms.

Problem Statement

- Sleep disorders often have overlapping symptoms, making accurate diagnosis difficult and manual EEG analysis slow and error-prone.
- Hence, there is a need for an automated and reliable system to efficiently classify different sleep disorders using EEG data.

Why It Matters?

- Early and accurate detection can prevent long-term health complications.
- Automation can save time for clinicians, improve screening, and make sleep-health evaluation more accessible.

Literature Review



Paper	Author(s)	Year	Contribution	Gaps / Limitations
Multimodal Learning for Sleep Disorders	S. Khanmohammadi et al.	2025	<ul style="list-style-type: none"> Combined EEG + EOG + multi-task learning to improve accuracy for multiple sleep disorders. Demonstrated that fusing modalities captures richer physiological patterns than single-sensor models. 	<ul style="list-style-type: none"> Requires complex PSG setup with multiple sensors. Not suitable for portable or single-channel consumer devices.
Functional connectivity-based classification of rapid eye movement sleep behavior disorder	S. Srivastava et al.	2024	<ul style="list-style-type: none"> Used resting-state fMRI connectivity in iRBD patients and healthy controls. Applied Random Forest for feature selection, then classified with logistic regression or SVM. 	<ul style="list-style-type: none"> Moderate accuracy ($\approx 65\text{--}70\%$) limits clinical reliability. Resting-state fMRI may not capture true REM sleep abnormalities; small sample size reduces generalizability.
Explainable CNN for Sleep Apnea Detection	L. D. Barnes et al.	2022	<ul style="list-style-type: none"> Created a CNN with explainability tools to identify apnea-related EEG patterns. Demonstrated feasibility of single-channel EEG for diagnosing sleep apnea. 	<ul style="list-style-type: none"> Focuses only on sleep apnea, not multi-disorder detection. Explainability still limited and not clinically validated.
CNN-based Automatic Sleep Staging	L. Zhuang et al.	2022	<ul style="list-style-type: none"> Achieved high sleep-stage classification accuracy using deep CNNs. Provides high-quality stage labels that can serve as features for detecting disorders later. 	<ul style="list-style-type: none"> Does not directly classify or analyze sleep disorders. Model depends heavily on accurate epoch labeling.
Bi-directional RNN Model for Sleep EEG	Z. Fu et al.	2022	<ul style="list-style-type: none"> Bi-directional RNN captures long-term temporal dependencies across the sleep cycle. Encoder-decoder architecture helps learn transitions between sleep states more effectively. 	<ul style="list-style-type: none"> Computationally heavy and slow to train. Requires large datasets to avoid overfitting.

Literature Review



Paper	Author(s)	Year	Contribution	Gaps / Limitations
AI-Enabled Algorithm for Automatic Classification of Sleep Disorders	E. Urtnasan et al.	2021	<ul style="list-style-type: none"> Proposed a deep-learning pipeline to classify multiple disorders like Insomnia, PLM, RBD, NFLE, etc. Demonstrated that multi-disorder classification using combined EEG/PSG signals is feasible. 	<ul style="list-style-type: none"> Limited dataset size reduces generalization. No strong clinical validation or real-world deployment tests.
1D-CNN + HMM for Single-Channel Sleep Staging	B. Yang et al.	2021	<ul style="list-style-type: none"> Achieved strong single-channel EEG sleep staging performance using CNN + HMM refinement. Demonstrated that lightweight architectures can still extract meaningful sleep-phase patterns. 	<ul style="list-style-type: none"> Staging ≠ disorder detection; requires disorder-labeled data. Cannot directly classify or detect specific sleep abnormalities.
Automated Identification of Sleep Disorder Types Using EEG	M. Sharma et al.	2021	<ul style="list-style-type: none"> Built a feature-extraction + ML pipeline to classify six disorder types from EEG signals. Showed that traditional ML + handcrafted features can still perform competitively. 	<ul style="list-style-type: none"> Heavy reliance on handcrafted features limits robustness. Performance decreases significantly on noisy or real-world EEG data.
1D CNN for Sleep Apnea (ECG-based)	H. Y. Chang et al.	2020	<ul style="list-style-type: none"> Designed a lightweight 1D CNN for detecting sleep apnea using ECG instead of EEG. Demonstrated high apnea detection accuracy with low computational cost. 	<ul style="list-style-type: none"> Not EEG-based, limiting relevance to EEG disorder studies. Only detects apnea; cannot generalize to multiple disorders.
Machine Learning for Sleep Apnea Detection – Review	S. S. Mostafa et al.	2019	<ul style="list-style-type: none"> Provided a comprehensive review of ML/DL methods, datasets, and challenges for apnea detection. Highlighted performance trends and data limitations across apnea-related studies. 	<ul style="list-style-type: none"> Focuses only on apnea, not other disorders. Offers limited insights for multi-disorder EEG research.



Dataset Used

🔗 Link: <https://www.kaggle.com/datasets/shrutimurarka/cap-sleep-unbalanced-dataset>

Dataset Size & Content:

- Recording center: Sleep Disorders Center, Ospedale Maggiore (Parma, Italy).
- Number of recordings: 108 polysomnographic(PSG) recordings.
- Channels per recording: At least 3 EEG channels + EOG, EMG (chin & tibial), respiration (airflow, thoracic/abdominal effort, SaO_2), ECG(sampling 100–200 Hz).
- Subject groups: 16 healthy (control) subjects + 92 pathological (sleep-disordered) subjects.
- Disorder breakdown: Includes subjects with NFLE(Nocturnal Frontal Lobe Epilepsy), RBD(REM Sleep Behavior Disorder), PLM(Periodic Limb Movement), insomnia, narcolepsy, sleep-disordered breathing, bruxism.

Annotations & Labels

- Sleep macrostructure scored according to standard sleep-stage rules (wake, NREM stages, REM) by experts.
- CAP (Cyclic Alternating Pattern) annotations: phases (A-phase subtypes A1, A2, A3; phase B) marked by neurologists per standard CAP scoring protocols.
- Labels allow linking EEG/PSG signal segments with normal vs various disordered sleep conditions.

Why This Dataset Fits For Sleep-Disorder Detection Projects

- Contains both healthy and multiple disorder types — useful for multi-class classification or disorder vs controlstudies and has rich, multi-modal data.
- Expert annotations of both sleep stages and CAP phases — helpful for staging, micro-structure analysis, and advanced disorder markers.



Dataset Preparation Continued..

1. Data Acquisition

- Collected EEG/PSG data from healthy subjects and patients with disorders (Insomnia, RBD, PLM, Narcolepsy, NFLE).
- Used standard-rate single-channel EEG recordings.

2. Pre-Processing Flow

- Cleaning:** Removed noise/artifacts; applied band-pass filtering.
- Segmentation:** Split EEG into fixed windows (e.g., 30-sec).
- Labeling:** Assigned each segment its disorder label from the dataset.
- Normalization:** Standardized signal amplitudes.
- Splitting:** Created balanced train/validation/test sets.

Subjects		Phase A				Phase B	Total
		A1	A2	A3	Total		
Healthy		4654	1551	2847	9052	62880	71862
Unhealthy	Insomnia	2932	1660	4162	8754	47055	55809
	Narcolepsy	2958	1593	4255	8806	45330	54136
	PLM	3990	2989	7670	14649	67080	81729
	RBD	11230	7350	20620	39200	206805	246005
	NFLE	25047	12596	23725	61368	295875	357243
	Total	46157	26188	60432	132777	662145	
Total		50811	27739	63279	141829	725025	866854

Total number of samples available after segmentation.



Dataset Preparation Continued..

Subjects		Phase A	Phase B	Total	
Healthy		4650	4650		9300
Unhealthy	Insomnia	930	930	1860	9300
	Narcolepsy	930	930	1860	
	PLM	930	930	1860	
	RBD	930	930	1860	
	NFLE	930	930	1860	
	Total	4650	4650		
Total		9300	9300		18600

Total number of samples used for CP1 classification(Normalised).

Subjects	Phase A	Phase B	Total
Insomnia	4779	4779	9558
Narcolepsy	4779	4779	9558
PLM	4779	4779	9558
RBD	4779	4779	9558
NFLE	4779	4779	9558
Total	23895	23895	47790

Total number of samples considered for CP2 classification



Proposed Methodology

A. End-to-End Deep Learning Pipeline

1. A 1D Convolutional Recurrent Neural Network (CRNN) takes raw single-channel EEG and automatically learns both spatial features (via CNN) and temporal dependencies (via LSTM).
2. This end-to-end approach removes the need for manual feature engineering, enabling the model to directly capture disorder-specific waveform patterns such as spindles and K-complexes.
 - a. Sleep spindles and K-complexes are two of the most informative EEG micro-events for sleep-disorder modeling.
 - b. **Sleep spindles** are brief 11–16 Hz bursts that indicate stable N2 sleep and reflect thalamocortical integrity; their absence, fragmentation, or abnormal frequency often signals conditions like insomnia or PLM.
 - c. **K-complexes**, on the other hand, are sharp high-amplitude waves followed by slow components, acting as markers of cortical arousal and sensory gating during sleep. Disorders such as RBD and NFLE frequently alter the shape, timing, or density of these events. By learning these patterns automatically, the CRNN captures disorder-specific EEG signatures without handcrafted features.
3. Combined CNN–LSTM learning, along with class-balanced training and optimized loss functions, ensures strong generalization and reliable performance across subjects.



Proposed Methodology

B. Two-Stage Hierarchical Classification

Stage 1 – Sleep Health Classification

- A lightweight CRNN first classifies each EEG segment as Healthy or Disordered, acting as a coarse screening layer.
- This stage is tuned for high sensitivity, ensuring disordered cases are not missed before entering Stage 2.

Stage 2 – Disorder Type Classification

- Only segments predicted as Disordered proceed to a deeper CRNN that identifies the specific disorder: Insomnia, Narcolepsy, RBD, PLM, or NFLE.
- This hierarchical design reduces misclassification and improves per-class accuracy by letting Stage 2 specialize in inter-disorder distinctions.

C. Feature Learning via CRNN

- CNN-Driven Spatial–Spectral Extraction: 1D-CNN layers automatically learn frequency- and morphology-based EEG patterns such as spindles, K-complexes, and micro-arousals, eliminating manual feature engineering.
- Temporal Dynamics via LSTM: LSTM layers capture long-range temporal flow across sleep cycles, enabling the model to combine short-term waveform events with broader EEG transitions for accurate disorder identification.



Proposed Methodology

D. CAP (Cyclic Alternating Pattern) Integration

- Sleep Instability Encoding: CAP A/B phase information is incorporated to quantify physiological sleep instability, which varies across disorders.
- CAP-Aligned Segmentation: Aligning EEG segments with CAP cycles improves temporal precision and enhances separability between visually similar disorders such as RBD, PLM, and NFLE.

E. Training & Optimization Strategy

- Robust Optimization & Regularization: Cross-entropy with Adam ensures stable training, while early stopping, dropout, and L2 regularization prevent overfitting and strengthen generalization to unseen subjects.
- Class-Balanced Learning: Weighted loss and balanced sampling address dataset imbalance, ensuring minority disorders (e.g., NFLE, Narcolepsy) are learned effectively and improving per-class recall.



Algorithm Flow: End-to-End Sleep Disorder Detection

1. Data Input & Pre-Processing

- Import raw single-channel EEG (100–200 Hz).
- Apply band-pass filtering (0.5–40 Hz), normalization, and 30-sec epoching.
- Extract and align CAP A/B phases for instability-aware segmentation.

2. Stage-1 CRNN: Healthy vs. Disordered Detection

- **1D-CNN** extracts spatial–spectral signatures: spindles, K-complexes, micro-arousals.
- **LSTM** captures temporal transitions within and across cycles.
- **Output:** Binary label to Healthy / Disordered using high-sensitivity thresholds.

3. Stage-2 CRNN: Disorder Type Classification

- Only disordered segments are forwarded.
- A deeper CRNN with expanded filters and recurrent depth classifies into:
- Insomnia, Narcolepsy, RBD, PLM, NFLE.
- CAP-guided segmentation sharpens distinctions in overlapping patterns.

4. Feature Integration & Fusion

- Concatenate CNN feature maps with LSTM temporal embeddings.
- Append CAP-derived instability metrics as auxiliary inputs.
- Fusion provides a combined representation of: short-term waveform events + long-term temporal flow + sleep instability signals.



Algorithm Flow: Continued..

5. Training Pipeline

- Uses weighted cross-entropy so rare disorders get higher importance.
- Adam optimizer with gradual learning-rate decay for stable convergence.
- Dropout + L2 regularization prevent overfitting; early stopping stops training when validation accuracy stops improving.
- Stratified mini-batches ensure every batch contains a balanced mix of disorder classes.

6. Inference & Decision Logic

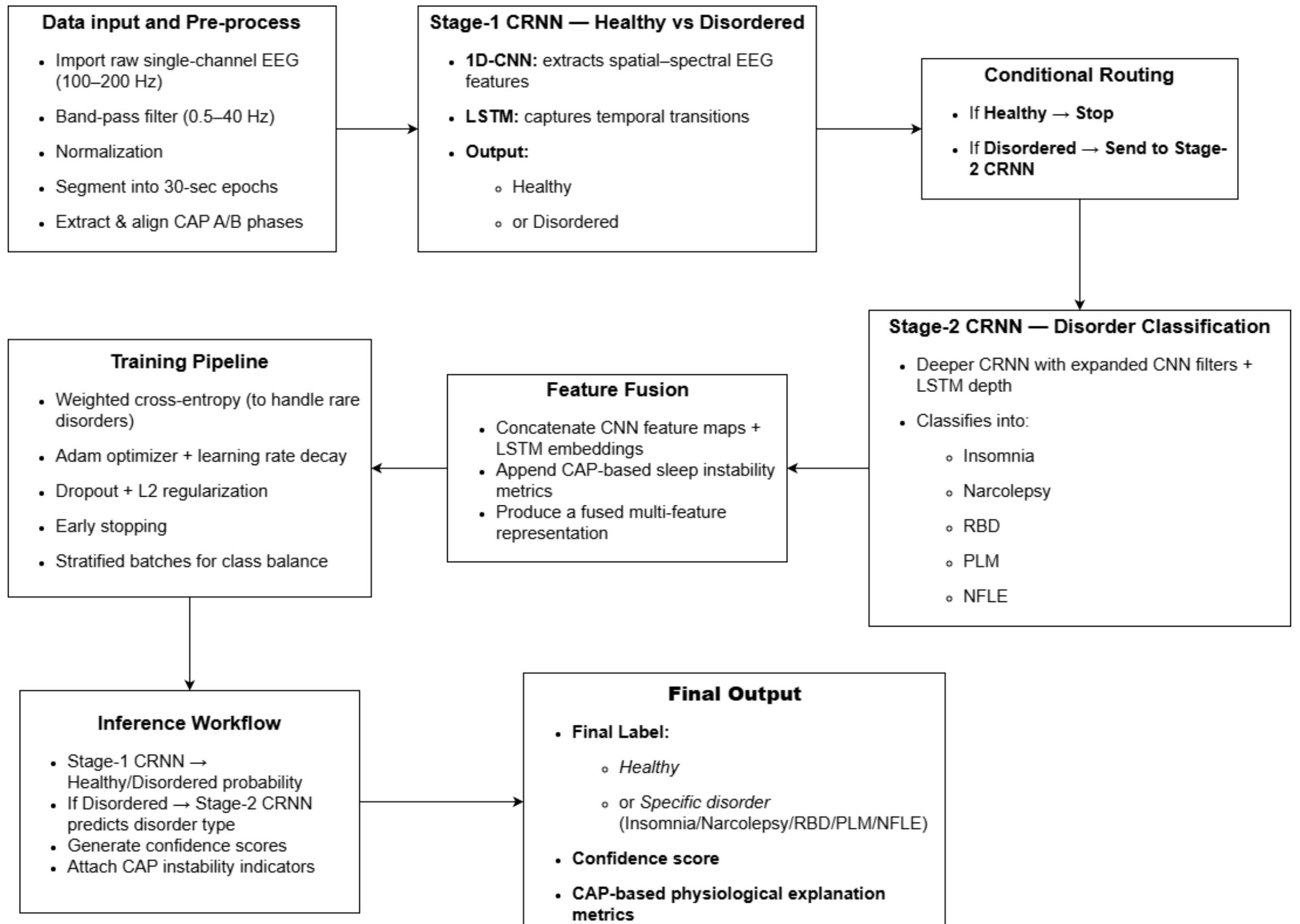
- **Stage 1:** First CRNN predicts Healthy vs Disordered using Softmax probabilities.
- If the probability of Healthy is above a threshold, the sample exits here.
- **Stage 2:** Only disordered segments go to the deeper CRNN, which predicts Insomnia / Narcolepsy / RBD / PLM / NFLE.
- Confidence scores (Softmax values) highlight uncertain or borderline predictions for review.

7. Output Layer & Reporting

- **Final output** = Healthy or specific disorder label, along with its confidence score.
- Additional CAP-based instability indicators (e.g., A-phase rate, CAP percentage) provide physiological context and support explainability.



Block Diagram



Experimental Metrics: Healthy-Unhealthy classification

117/117 - 1s - 1s/epoch - 9ms/step

Accuracy: 0.865932

Specificity: 0.844127

Precision: 0.855764

Sensitivity: 0.886842

F1 score: 0.871026

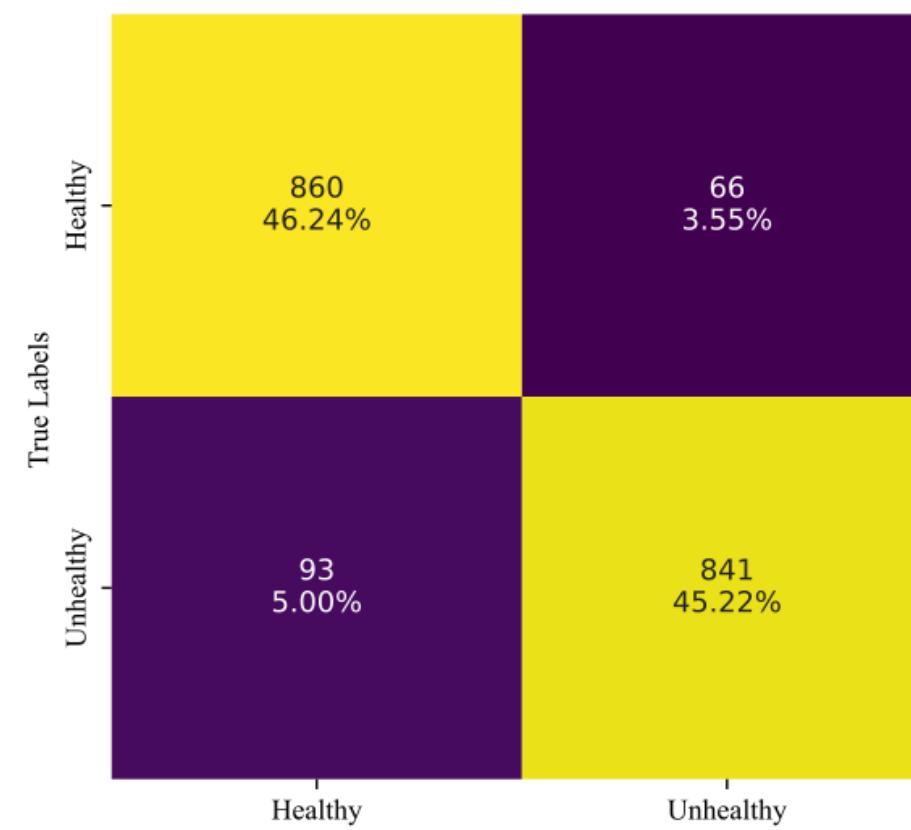
Cohens kappa: 0.731538

ROC AUC: 0.942347

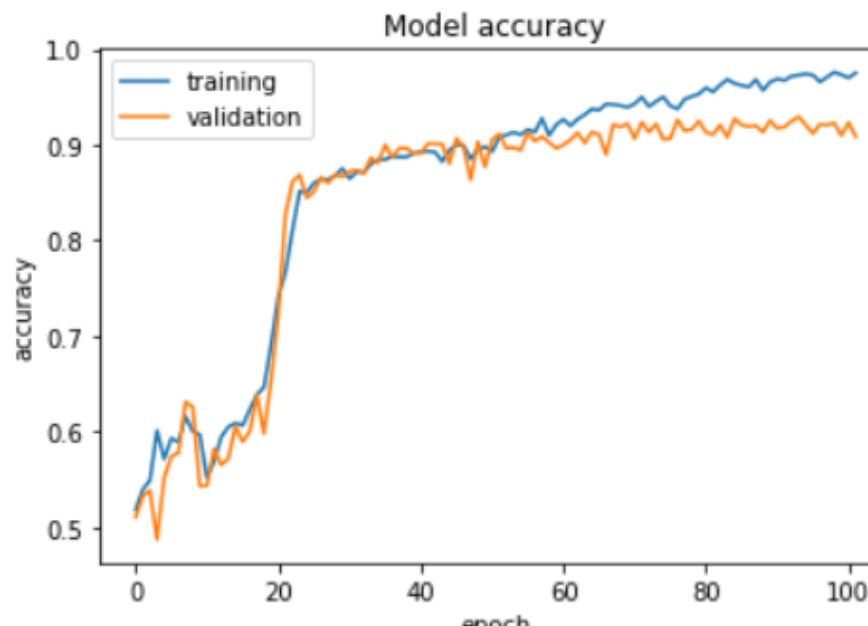
Total Samples Test: 3722

`[[1538 284]`

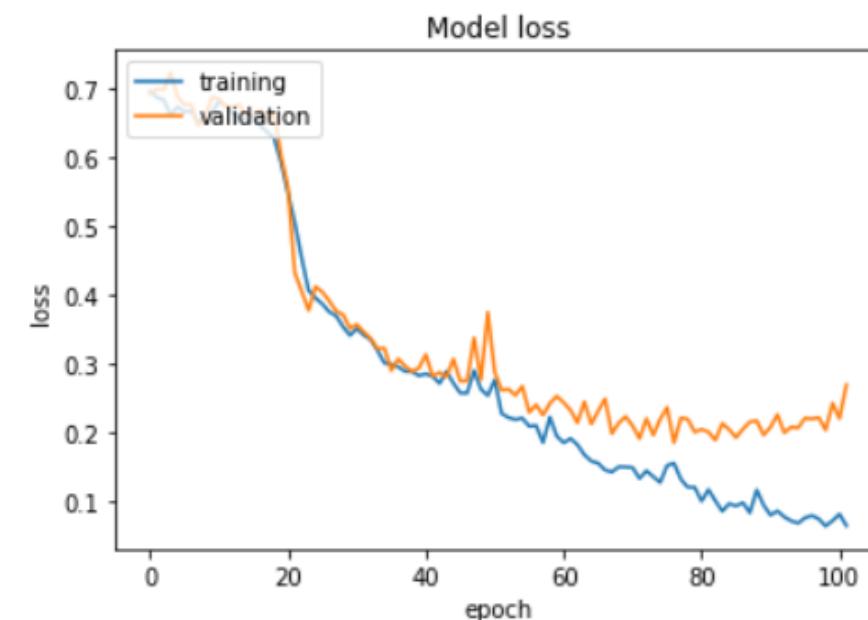
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Confusion matrix for healthy-unhealthy classification.

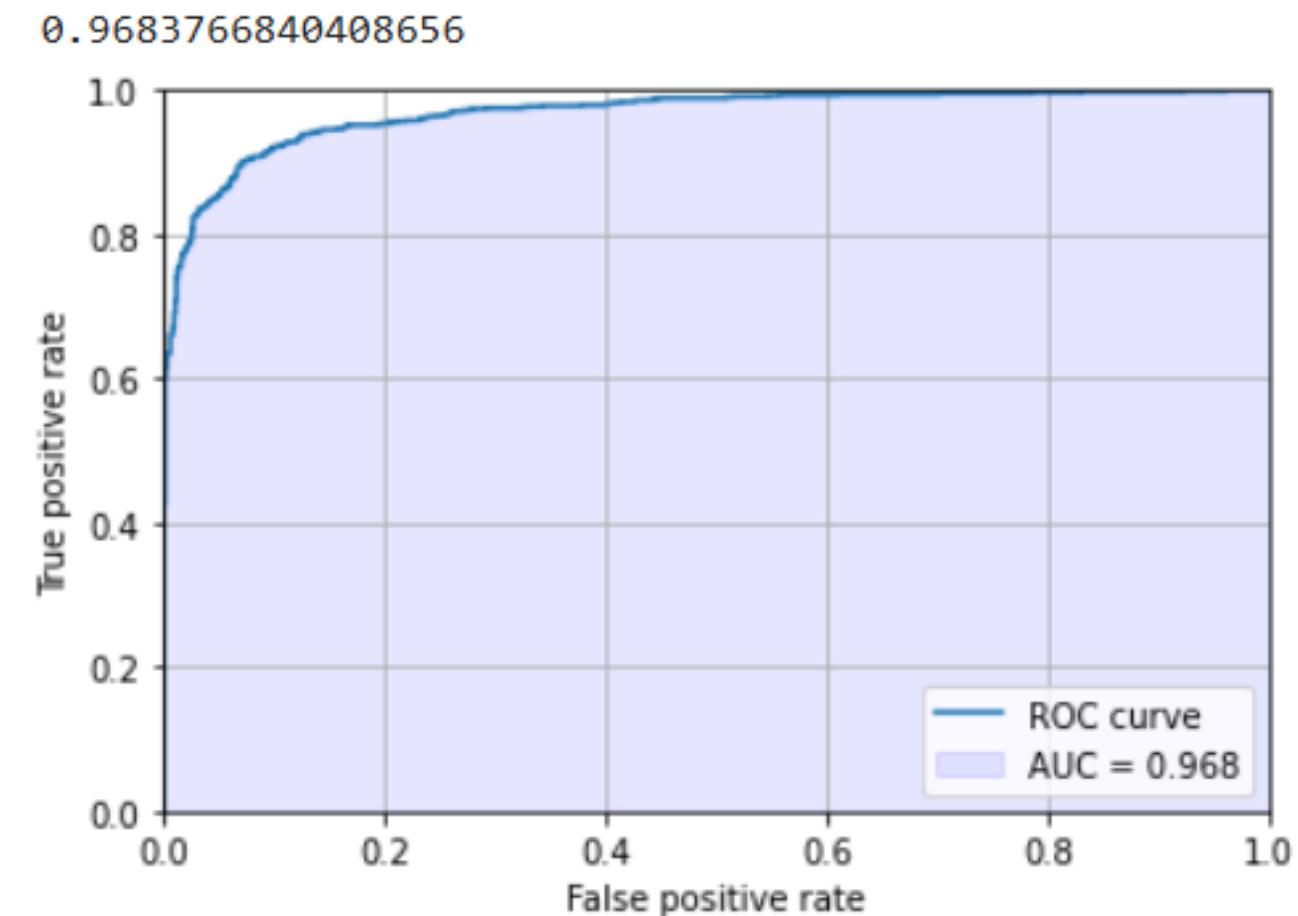


Accuracy graph for healthy-unhealthy classification



Training accuracy: 97.51344323158264
Validation accuracy: 90.86021780967712

Loss graph for healthy-unhealthy classification



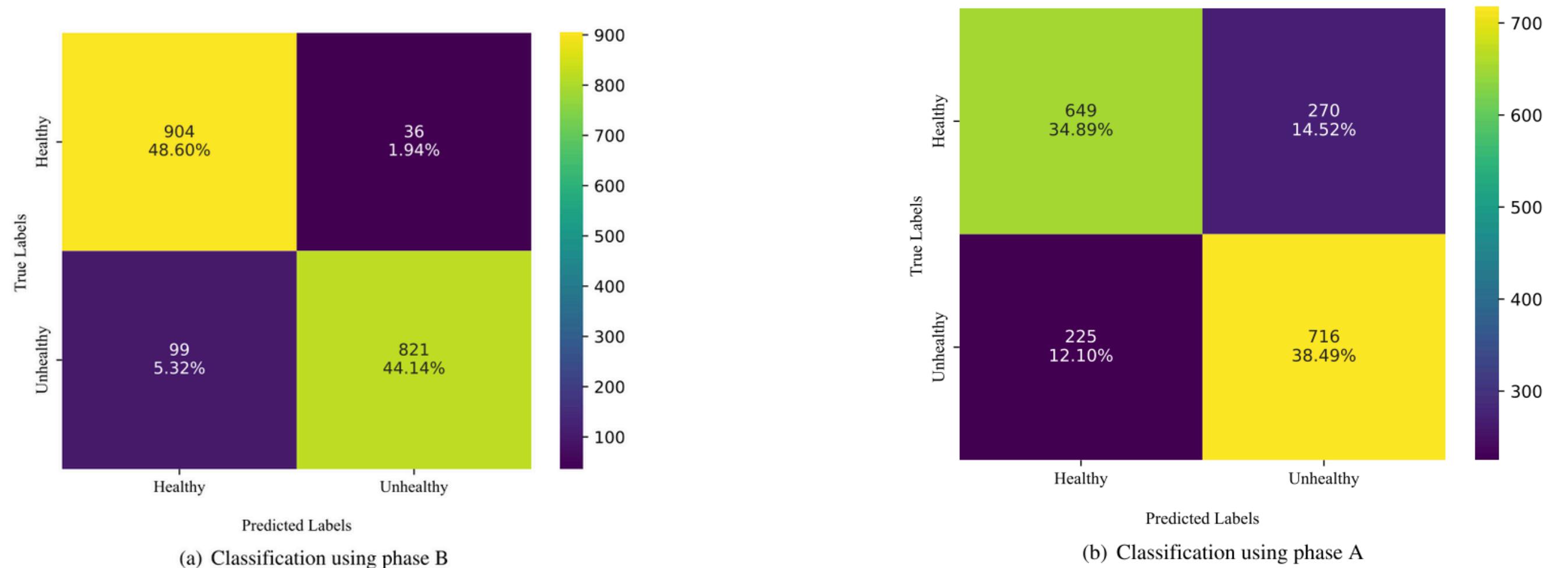
ROC curve
Healthy vs Unhealthy classification

Experimental Metrics

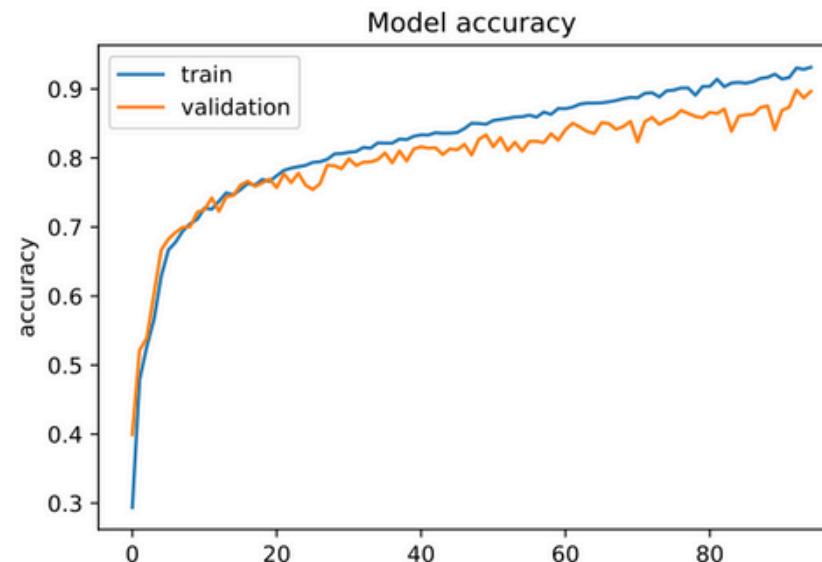


Dataset	Accuracy (%)			Performance parameters (%)				
	Train	Validation	Test	Precision	Specificity	Sensitivity	F1	AUC
Both phases	97.51	90.86	91.45	92.72	92.87	90.04	91.36	96.83
Phase B	96.53	93.34	92.79	95.79	96.17	89.23	92.40	97.51
Phase A	92.28	73.79	73.38	72.61	70.62	76.08	74.31	80.08

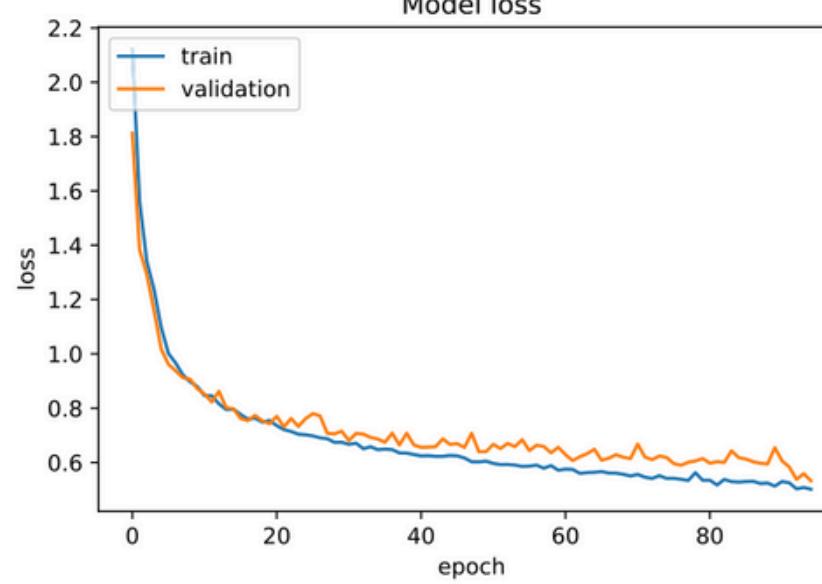
Model accuracies and performance parameters for CP1 using 1D CNN + LSTM.



Evaluation Metrics: Disease Classification



(a) Accuracy graph for disease detection



(b) Loss graph for disease detection

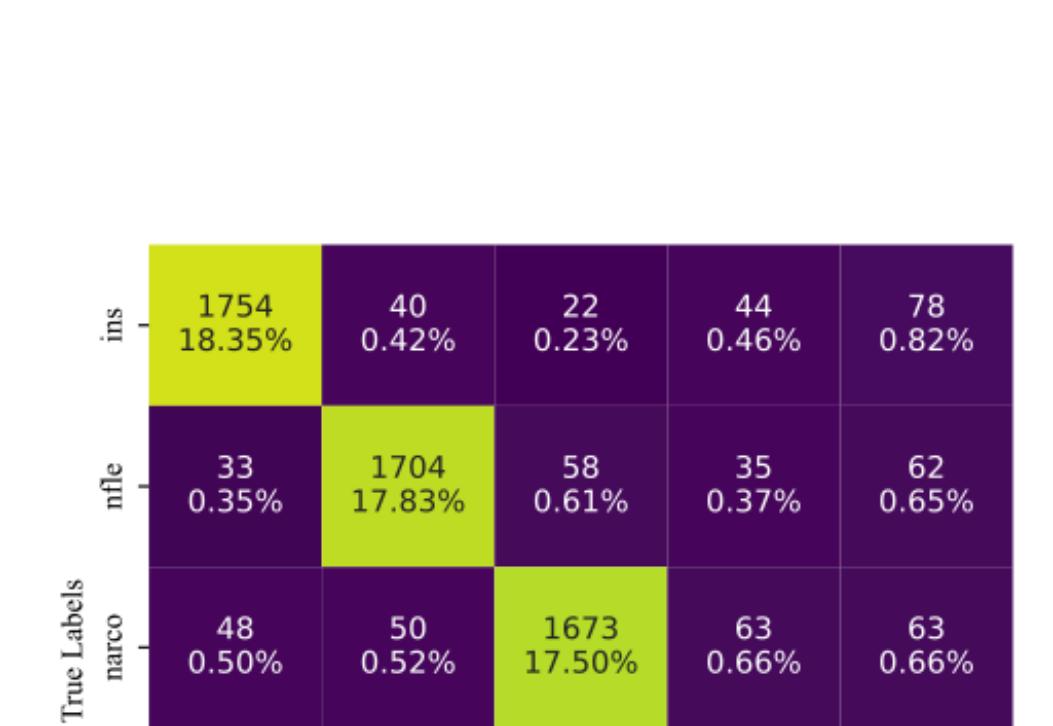
Performance graphs during training for disease dataset.



FIGURE 11. Confusion matrix for disease classification using dataset of B phase.



FIGURE 12. Confusion matrix for disease classification using dataset of A phase.



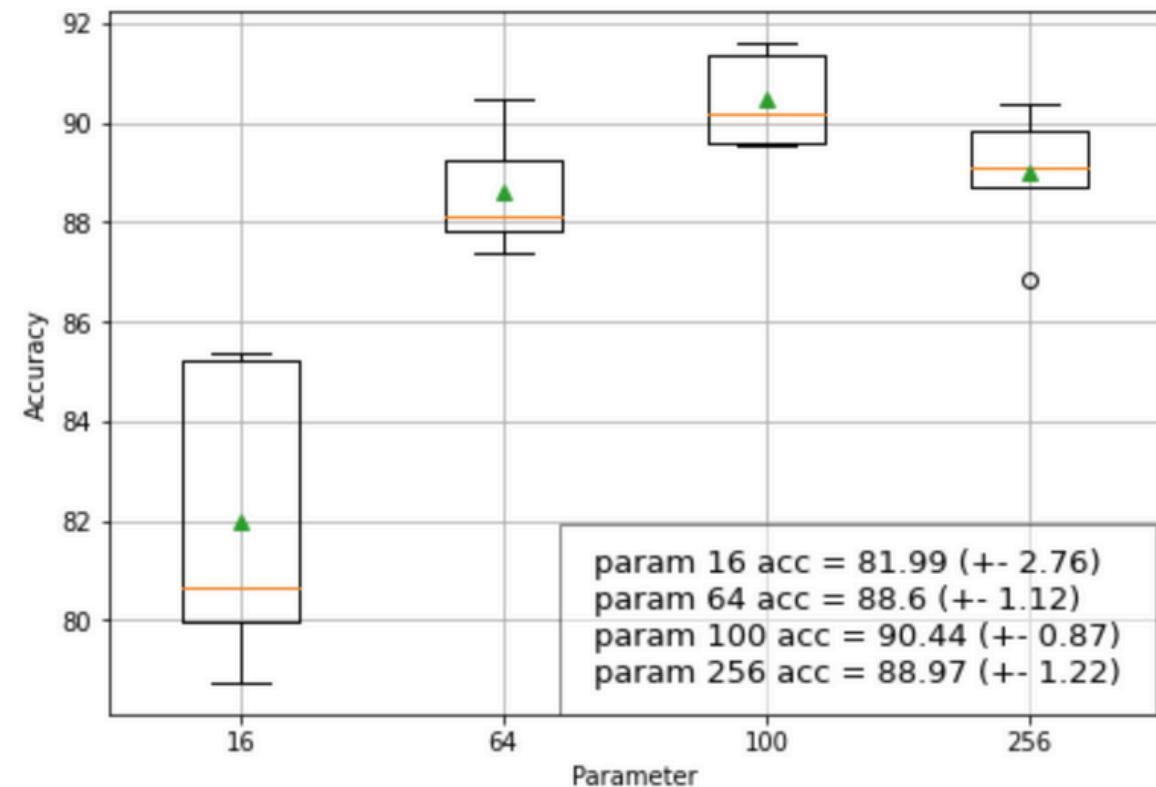
Confusion matrix for disease classification using dataset of both phases



Improving Accuracy Results

Hyperparameter Tuning

Fold Parameter	LSTM Units	Batch Size	Epochs	Avg Accuracy (%)	Avg Loss	Notes
Param 16	16	75	50	81.80653874204	0.18193461258	Small LSTM units; lowest capacity
Param 64	128	75	50	87.0698916912078	0.319260376691818	Medium LSTM units; better accuracy
Param 100	100	75	50	90.443547964096	0.246862736344337	Original model; balanced accuracy
Param 256	256	75	50	89.4220423698425	0.274168720841407	Largest LSTM units; highest model capacity



Hyperparameter optimization for the LSTM layer.

Conclusion



- This study confirms that automated sleep-disorder detection from single-channel EEG is both practical and clinically meaningful. Using a 1D-CNN and LSTM-based CRNN architecture, the model successfully learns key temporal-spectral patterns of sleep, capturing disorder-specific signatures such as spindle irregularities, K-complex deviations, REM instability, and PLM-related micro-arousals without relying on handcrafted features.
- Guided by CAP-aligned segmentation and a hierarchical two-stage classification approach, the framework remains physiologically grounded, improving both diagnostic accuracy and interpretability by aligning predictions with real sleep-regulation mechanisms.
- On the CAP dataset (derived from leg-movement signals), the original Param-100 model achieved a balanced accuracy of 90.44% with a loss of 0.2468, demonstrating strong performance for a single-channel system.
- Overall, the work lays the foundation for next-generation intelligent sleep-analysis tools—offering faster, more explainable, and more accessible diagnostic support. With further refinement, such models can reduce clinical workload, enable earlier disorder detection, and ultimately enhance patient outcomes in sleep medicine.



Future Scope

- **Nature-Based Optimization Techniques:** In future work, the model will replace the Adam optimizer with nature-inspired algorithms such as Grey Wolf, Firefly, Whale, or PSO. These optimizers offer stronger global search ability and help avoid local minima, which can improve training on complex EEG data.
- **Advanced Deep Learning Architectures:** Instead of the current CRNN, future versions can use deeper models like VGGNet, ResNet, or EfficientNet for better feature extraction. These CNN backbones can capture richer temporal–spatial EEG patterns.
- **Enhanced Temporal Modeling:** Standard LSTM modules can be replaced with BiLSTM or hybrid BiLSTM-TCN structures to capture long-range temporal patterns more effectively. These architectures help the model learn forward and backward EEG dependencies.
- **Real-Time, Lightweight Deployment:** Future versions can optimize the model using pruning and quantization so it can run in real-time on wearable devices, along with simple explainability tools for clinicians.



References

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THANK YOU

