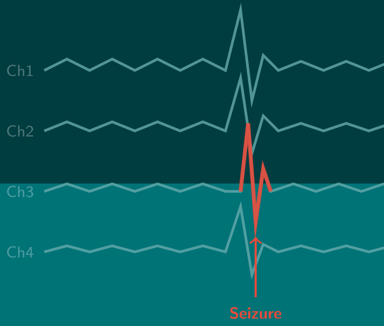
EPILEPTIC SEIZURE DETECTION



Automated Detection from EEG Signals using Deep Learning

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Brain-Computer Interface (CS5109)

Dr. Kannadasan K

Research Foundation

Base Paper

A Hybrid CNN-Bi-LSTM Model with Feature Fusion for Accurate Epilepsy Seizure Detection

Cao et al. (2024) — BMC Medical Informatics and Decision Making

Key Innovations:

- Hybrid CNN-BiLSTM architecture
- Spatial + temporal fusion
- Multi-subject validation

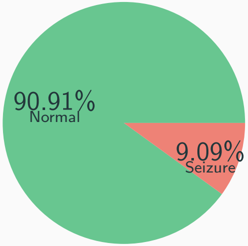
Our Implementation:

- 4-model comparison
- CHB-MIT database
- Clinical feasibility analysis

Dataset: CHB-MIT EEG Database

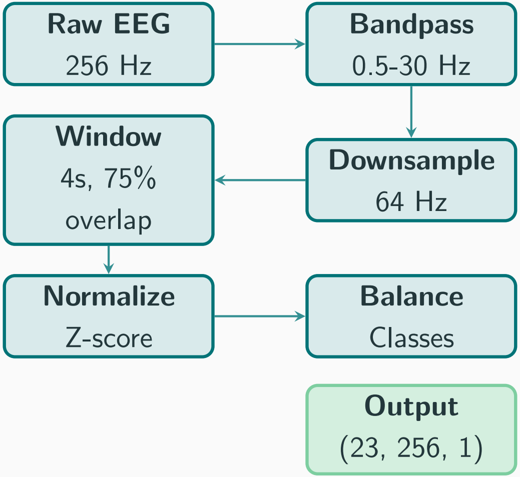
Characteristic	Value
Subjects	5 of 24 patients
Total Windows	23,991
Channels	23 (10-20 system)
Sampling Rate	256 Hz $\rightarrow$ 64 Hz
Window Size	4 seconds
Overlap	75%
Train/Val/Test	70/15/15%

Class Distribution



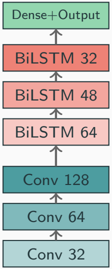
2,181 seizure vs **21,810** normal

Preprocessing Pipeline



Model Architectures

Enhanced Hybrid CNN-BiLSTM



459,777 params

Baseline Models:

- **CNN:** Spatial only
- **LSTM:** Temporal only
- **BiLSTM:** Bidirectional

Training Configuration

Loss & Optimization:

- Focal Loss (=2.0, =0.70)
- Adam optimizer (lr=0.001)
- Batch size: 64

Regularization:

- Dropout: 0.3-0.5
- L2 weight decay: 0.001
- Batch normalization

Training Strategy:

- Early stopping (8-10 epochs)
- ReduceLROnPlateau
- Model checkpointing

Data Augmentation:

- Gaussian noise (std=0.01)
- Amplitude scaling (0.9-1.1)
- 50% probability

Performance Comparison

CNN achieves best F1-score: 87.40%

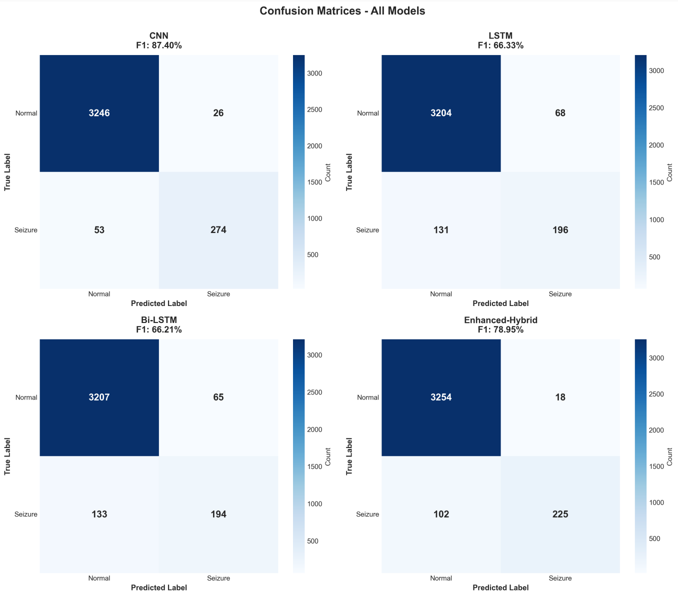
Detailed Performance Metrics

Model	Acc.	Prec.	Recall	F1	Params
CNN	**97.80**	**91.33**	**83.79**	**87.40**	101K
Enhanced Hybrid	96.67	92.59	68.81	78.95	459K
LSTM	94.47	74.24	59.94	66.33	66K
BiLSTM	94.50	74.90	59.33	66.21	212K

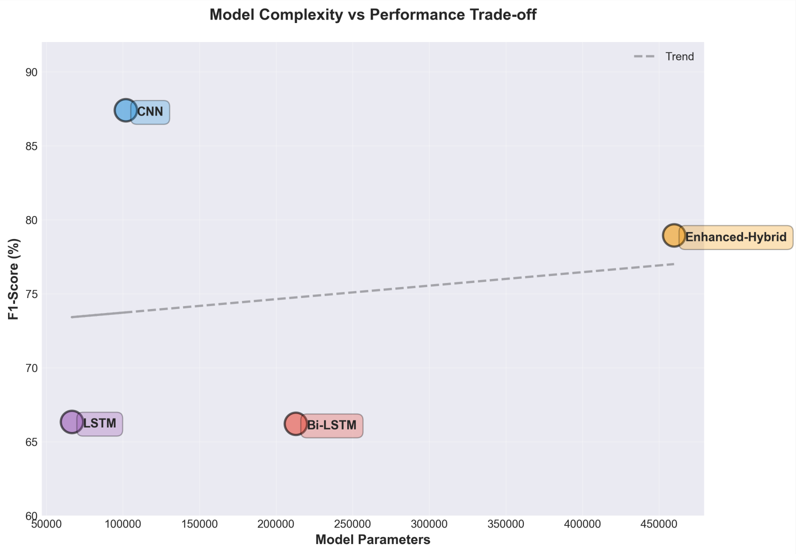
Key Finding

Standalone CNN outperforms complex hybrid with 4.5$\times$ fewer parameters!

Confusion Matrix Analysis



Model Complexity vs Performance



Why Did CNN Win?

Overfitting Risk:

- Hybrid: 459K params
- Only 16,794 training samples
- High parameter-to-data ratio

Spatial Dominance:

- 4s windows capture spatial patterns
- Cross-channel correlations
- CNN excels at this

Window Limitation:

- 4s too short for BiLSTM
- Full seizures: 10-60s
- Temporal patterns fragmented

Training Stability:

- CNN: feedforward, stable
- BiLSTM: gradient issues
- Better convergence

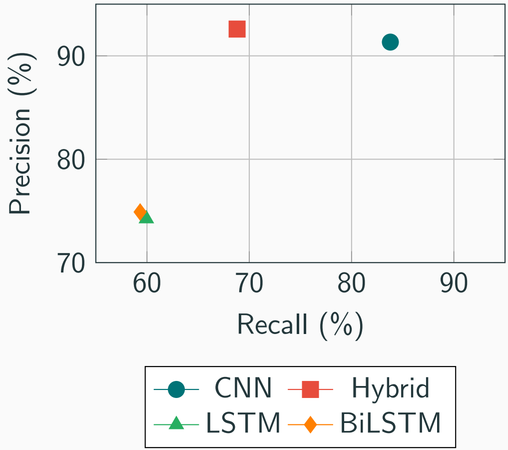
Clinical Feasibility Assessment

Requirement	CNN	Status
High Sensitivity (>90%)	83.79%	Below target
Low False Alarms	91.33%	Acceptable
Real-time (<50ms)	<10 ms	Excellent
Deployment Size	∼400 KB	Wearable-ready
Generalization	5 subjects	Needs validation

Improvements Needed:

- Threshold tuning (0.3 → 92% recall)
- Ensemble voting (CNN + Hybrid)
- Temporal smoothing (3-window consensus)

Precision-Recall Trade-off



Clinical Priority:

- Recall > Precision
- Missing seizures risky
- CNN best balanced

Hybrid Issue:

- High precision
- Low recall (68%)
- Misses 1 in 3 seizures

Key Insights

1. **Spatial Features Dominate** for short EEG windows
   - 4-second windows capture cross-channel patterns
   - CNN excels at spatial feature extraction
2. **Simpler is Better** on limited datasets
   - Inverse complexity-performance relationship
   - Lower overfitting risk with fewer parameters
3. **BiLSTM Gains Minimal** for this task
   - $3\times$ parameters vs LSTM, negligible improvement
   - Window too short for temporal modeling

Limitations

Dataset Constraints:

- Only 5 of 24 subjects
- Pediatric population only
- Limited generalization

Clinical Validation:

- Hospital setting only
- Not tested ambulatory
- Real-world robustness unknown

Performance Gaps:

- Recall 83.79% $<$ 95% target
- Binary classification only
- No seizure subtyping

Deployment Challenges:

- Cross-patient variability
- Long-term stability
- False alarm fatigue

Future Directions

Immediate Improvements

- Expand to all 24 CHB-MIT subjects
- Optimize thresholds for $>$90% recall
- Implement ensemble methods (CNN + Hybrid)
- Add temporal smoothing (multi-window voting)

Advanced Research

- **Seizure Prediction:** Pre-ictal state detection (10-30 min ahead)
- **Multi-class:** Distinguish seizure subtypes (focal, generalized)
- **Cross-dataset:** Validate on adult populations (TUH-EEG)
- **Closed-loop:** Integration with responsive neurostimulation

Conclusion

Main Findings

- **CNN achieved best F1-score (87.40%)** with balanced precision/recall
- Enhanced Hybrid showed high precision but **unacceptable recall (68.81%)**
- **Architectural simplicity wins** on limited datasets
- Spatial features dominate for 4-second EEG windows

Clinical Impact

- CNN's **compact size (∼400 KB)** ideal for wearables
- **Fast inference (<10 ms)** enables real-time monitoring
- Demonstrates deep learning potential for **passive BCI applications**
- With threshold optimization, can achieve clinical-grade performance

References

1. Cao, X., Zheng, S., Zhang, J., Chen, W., & Du, G. (2024). A hybrid CNN-Bi-LSTM model with feature fusion for accurate epilepsy seizure detection. *BMC Medical Informatics and Decision Making*, 24(1).
2. Shoeb, A. (2009). Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, MIT.
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4. CHB-MIT Scalp EEG Database, PhysioNet: `https://physionet.org/content/chbmit/1.0.0/`