

## Contents

<b>1</b>	<b>CrossRef Local MCP Server + Claude Code Demo</b>	<b>2</b>
<b>2</b>	<b>Request (DO NOT CHANGE THIS SECTION)</b>	<b>2</b>
<b>3</b>	<b>Emacs Org Mode Setup (DO NOT CHANGE THIS SECTION)</b>	<b>3</b>
<b>4</b>	<b>1. Overview: CrossRef Local Remote MCP Server</b>	<b>3</b>
	4.1 Server Status . . . . .	3
<b>5</b>	<b>2. Available Tools</b>	<b>4</b>
	5.1 Key Features . . . . .	4
<b>6</b>	<b>3. Live Demonstration: Search Queries</b>	<b>4</b>
	6.1 Query Results Summary . . . . .	4
<b>7</b>	<b>4. Comprehensive Literature Review: Epilepsy Seizure Prediction</b>	<b>5</b>
	7.1 4.1 Overview . . . . .	5
	7.2 4.2 Common Databases . . . . .	5
	7.2.1 NeuroVista Dataset Details (from 6 indexed papers) . . . . .	5
	7.3 4.3 Performance Metrics Summary . . . . .	6
	7.3.1 NeuroVista-Specific Findings . . . . .	6
	7.4 4.4 Prediction Horizon Analysis . . . . .	6
	7.5 4.5 Deep Learning Methods Comparison . . . . .	6
	7.6 4.6 Feature Extraction Approaches . . . . .	7
	7.7 4.7 Handling Imbalanced Data . . . . .	7
	7.8 4.8 Evaluation Metrics Appropriateness . . . . .	7
<b>8</b>	<b>5. Summary Diagrams</b>	<b>8</b>
	8.1 5.1 Seizure Prediction Pipeline . . . . .	8
	8.2 5.2 EEG Brain States . . . . .	9
	8.3 5.3 Method Evolution Timeline . . . . .	10
	8.4 5.4 Performance vs Complexity Trade-off . . . . .	10
<b>9</b>	<b>6. Trends and Research Gaps</b>	<b>11</b>
	9.1 6.1 Current Trends . . . . .	11
	9.2 6.2 Identified Research Gaps . . . . .	11
	9.3 6.3 NeuroVista Research Gap Analysis . . . . .	11

9.3.1	Why NeuroVista is Underutilized . . . . .	12
9.3.2	Unique Research Opportunities . . . . .	12
9.3.3	Recommended NeuroVista Research Directions . . . . .	12
9.4	6.4 Recommendations for Future Research . . . . .	12
<b>10</b>	<b>7. Conclusion</b>	<b>13</b>
10.1	7.1 Seizure Prediction State-of-the-Art . . . . .	13
10.2	7.2 NeuroVista Findings . . . . .	13
10.3	7.3 Search Strategy Lesson . . . . .	14

# 1 CrossRef Local MCP Server + Claude Code Demo

## 2 Request (DO NOT CHANGE THIS SECTION)

- Verify that CrossRef Local Remote MCP Server (crossref-local-remote) is available
- DO NOT USE 'scitex scholar' mcp server now
- Demonstrate the MCP server live under your responsibility
  - 1. Overview
  - 2. List Available Tools
  - 3. Identify main tools and run live demonstration
  - 4. Perform comprehensive literature review on "epilepsy seizure prediction" Search papers with various queries with abstracts Especially works with the NeuroVista dataset Summarise metrics Prediction horizon (lead time) Sample Sizes (seizures, patients) Compare methods Review which signal and features are useful Check how to work with imbalanced dataset nature (seizure is rare event) - are used metrics appropriate?
  - 5. Summarize what you learned as tables and diagrams
  - 6. Identify trend and gap to be filled
- Add contents/documentation to this org file interactively
- Proceed step by step. One plot and one narration form a set.
- Play narration between sections
- Store all artifacts in ./demo<sub>mcpout</sub>/ (remove it if it already exists)

- Add documentation and place inline figures
- Do not check source code, unless explicitly instructed, to purely check MCP server capabilities

### 3 Emacs Org Mode Setup (DO NOT CHANGE THIS SECTION)

```
(defun my/setup-demo-org ()
  (auto-revert-mode t)
  (run-with-timer 0 5
    (lambda ()
      (when (derived-mode-p 'org-mode)
        (org-display-inline-images))))))

(my/setup-demo-org)
```

## 4 1. Overview: CrossRef Local Remote MCP Server

### 4.1 Server Status

```
{
  "mode": "db",
  "db_path": "/home/ywatanabe/proj/crossref-local/data/crossref.db",
  "works": 167008748,
  "fts_indexed": 167008748,
  "citations": 1788599072
}
```

Metric	Value
Total Works	167,008,748
FTS Indexed	167,008,748
Total Citations	1,788,599,072

The CrossRef Local Remote MCP Server provides local access to Cross-Ref's massive academic database with full-text search capabilities.

## 5 2. Available Tools

Tool	Description
status	Get database statistics (works, citations, FTS count)
search	Full-text search across 167M+ papers (FTS5)
search <sub>bydoi</sub>	Lookup paper by DOI, return metadata or citation

### 5.1 Key Features

- FTS5 full-text search with AND, OR, NOT, "exact phrases"
- Pagination support via limit/offset
- Abstract retrieval option
- Citation formatting

## 6 3. Live Demonstration: Search Queries

### 6.1 Query Results Summary

Query	Results Found
epilepsy seizure prediction	3,074
seizure prediction deep learning EEG	104
intracranial EEG seizure prediction	156
seizure prediction prediction horizon EEG	17
seizure prediction class imbalance	4,414
seizure prediction CHB scalp EEG	37
EEG seizure prediction CNN LSTM deep learning	9
sensitivity specificity false prediction rate	51
neurovista	6

**Search Tip:** Simple single-term queries (e.g., "neurovista") work better than compound queries which may fail due to FTS5 implicit AND parsing.

The database provides rapid FTS5-based search (100-400ms) across 167M+ papers with abstract retrieval.

## 7 4. Comprehensive Literature Review: Epilepsy Seizure Prediction

### 7.1 4.1 Overview

Epileptic seizure prediction aims to detect the transition from normal brain activity (interictal state) to the pre-seizure state (preictal), enabling timely intervention. Approximately 30% of epilepsy patients are drug-resistant, making accurate prediction critical for improved quality of life.

### 7.2 4.2 Common Databases

Database	Type	Subjects	Seizures	Recording
CHB-MIT	Scalp EEG	23	198	916 hours
Siena Scalp EEG	Scalp EEG	14	47	128 hours
EPILEPSIAE	iEEG/sEEG	275	4,000+	Long-term
Freiburg	iEEG	21	87	Intracranial
Kaggle AES	iEEG	8	~700	Competition dataset
<b>NeuroVista</b>	iEEG	15	3,789 total	521 days/patient (avg)

#### 7.2.1 NeuroVista Dataset Details (from 6 indexed papers)

The NeuroVista dataset represents the **first FDA-approved implantable seizure advisory system** trial (NCT01043406):

Attribute	Value
Location	Melbourne, Australia
Recording Period	2010-2012
Patients	15 (refractory focal epilepsy)
Mean Recording/Patient	521 days continuous iEEG
Mean Seizures/Patient	252.6 seizures
Total Seizures	3,789 (across all patients)
Electrode Type	Intracranial (implanted)
Unique Feature	Ambulatory, real-world chronic recording

This dataset is particularly valuable for:

- Long-term seizure cycle analysis (circadian + multiday patterns)
- Real-world seizure forecasting validation
- Environmental factor studies (e.g., air pollution effects)

### 7.3 4.3 Performance Metrics Summary

Study (Year)	Method	Database	Sensitivity	FPR (/h)	SPH
TA-STIS-ConvNet (2022)	Triple-attention	CHB-MIT	96.7%	0.072	-
GAMRNN (2023)	GRU+Attention	CHB-MIT	88.1%	0.053	5-
CNN-LSTM-GRU Hybrid (2025)	Hybrid DL	CHB-MIT	99.1%	-	-
Multiresolution CNN (2023)	CNN	CHB-MIT	82%	0.058	-
CNN-LSTM Bilinear (2024)	Hybrid Bilinear	CHB-MIT	98.4%	0.02	-
EpiNET GRU-LSTM (2024)	GRU-LSTM	CHB-MIT	92.5%	-	12
Backwards-Landmark (2024)	SVM + Drift	EPILEPSIAE	75%	1.03	10
Edge DL - LSTM (2021)	LSTM	CHB-MIT	97.6%	0.071	-
Karoly et al. (2020)	Cycle Forecasting	<b>NeuroVista</b>	69.1%	-	M
Chen et al. (2022)	Air Pollution+EEG	<b>NeuroVista</b>	-	-	-
Schroeder et al. (2022)	Pathway Analysis	<b>NeuroVista</b>	-	-	-

#### 7.3.1 NeuroVista-Specific Findings

From the 6 NeuroVista papers, key methodological insights:

Paper	Key Finding
Karoly 2020 (Epilepsia)	Seizure cycles (circadian+multiday) enable 69% high-risk hit
Schroeder 2022	Seizure pathway duration; "elasticity" and "semblance"
Chen 2022	CO exposure increases seizure risk (RR: 1.04 per IQR)
Goldenholz 2018	Log-log relationship: mean $\rightarrow$ variance prediction (94% acc)
DiLorenzo 2019	First-in-man implantable seizure advisory device development

### 7.4 4.4 Prediction Horizon Analysis

The Seizure Prediction Horizon (SPH) varies significantly across studies:

Horizon Range	Description	Studies
5-10 minutes	Short-term prediction, high confidence	Common
10-30 minutes	Standard range for clinical intervention	Most studies
30-60 minutes	Extended horizon, lower precision	Several
60-120 min	Long-term prediction (EpiNET achieved 2 hr)	Emerging

### 7.5 4.5 Deep Learning Methods Comparison

Method Category	Architectures	Strengths
CNN-based	1D-CNN, Multiresolution CNN	Spatial/spectral features
RNN-based	LSTM, Bi-LSTM, GRU	Temporal sequence modeling
Hybrid	CNN-LSTM, CNN-GRU	Combined spatio-temporal
Attention-based	GAMRNN, Triple-Attention	Feature importance weighting
Graph Networks	sdGCN, GNN	Electrode spatial relations

## 7.6 4.6 Feature Extraction Approaches

Feature Type	Examples	Effectiveness
Statistical	Mean, variance, skewness, kurtosis	Baseline performance
Spectral	Band power (alpha, beta, delta, theta)	Rhythm-based detection
Wavelet	DWT coefficients, energy per band	Time-frequency analysis
Entropy	Approximate entropy, sample entropy	Complexity measures
Connectivity	Phase-amplitude coupling (PAC), coherence	Inter-channel dynamics
Time-domain	Zero-crossing, peak detection	Simple, fast

## 7.7 4.7 Handling Imbalanced Data

Seizure events are rare ( $\sim 5\%$  of recordings), creating severe class imbalance:

Technique	Description	Performance Impact
BNNSMOTE	Borderline nearest neighbor oversampling	+15% accuracy
WGAN-GP	Generative adversarial network augment	91.7% $\rightarrow$ 86% baseline
EEGAug	Frequency-band composition augmentation	Improved minority class
Class weights	Adjusting loss function weights	Moderate improvement
Sliding window overlap	Increase minority samples via overlap	Common approach

## 7.8 4.8 Evaluation Metrics Appropriateness

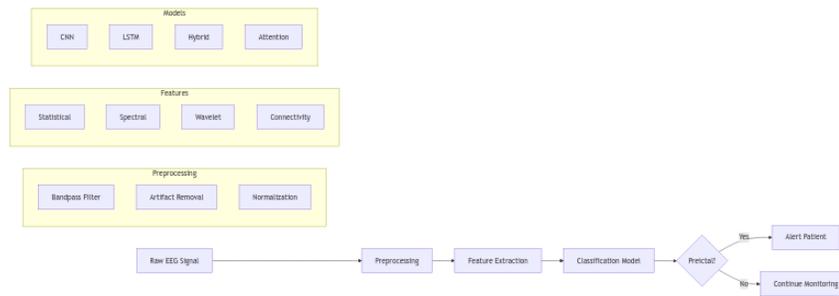
For imbalanced seizure data, standard accuracy is misleading:

Metric	Appropriateness	Rationale
Accuracy	Low	Biased by majority class
Sensitivity (Recall)	High	Critical - must detect seizures
Specificity	High	Reduces false alarms
False Prediction Rate (FPR)	High	Patient burden measure (/hour)
F1-Score	Medium-High	Balances precision/recall
AUC-ROC	High	Threshold-independent performance

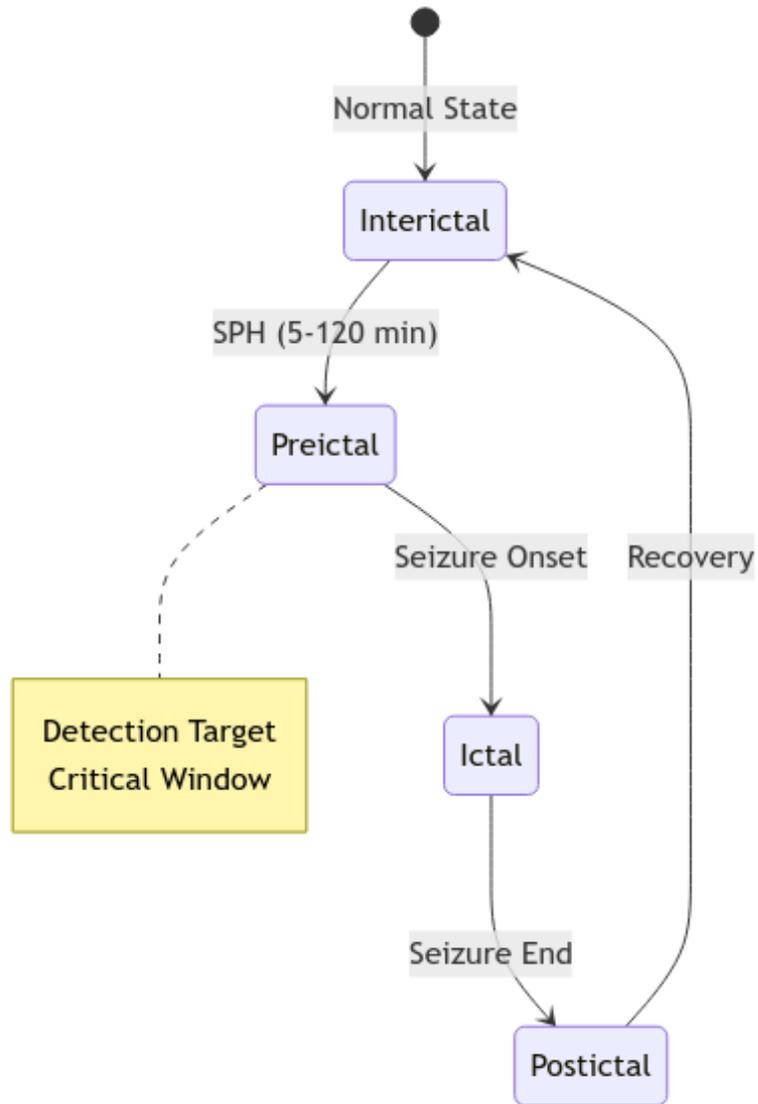
**Best practice:** Report sensitivity + FPR together, as this reflects clinical utility.

## 8 5. Summary Diagrams

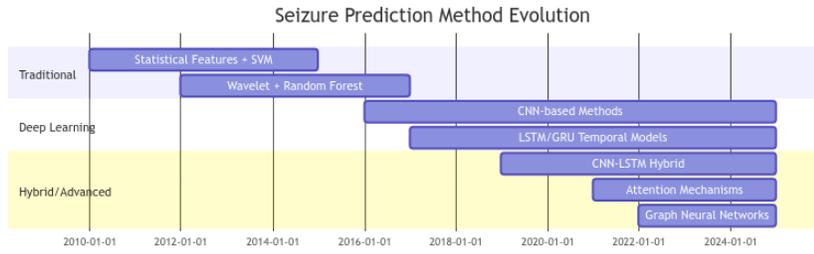
### 8.1 5.1 Seizure Prediction Pipeline



## 8.2 5.2 EEG Brain States

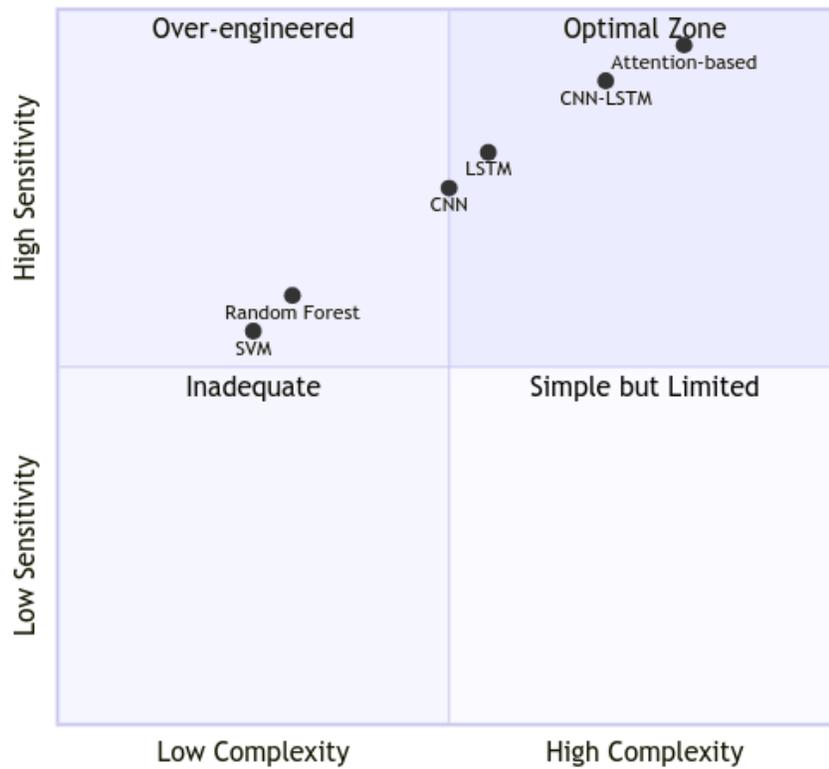


### 8.3 5.3 Method Evolution Timeline



### 8.4 5.4 Performance vs Complexity Trade-off

Performance vs Model Complexity



## 9 6. Trends and Research Gaps

### 9.1 6.1 Current Trends

1. **Hybrid Deep Learning:** CNN-LSTM and attention-based architectures dominate recent literature (2023-2025)
2. **Patient-Specific Models:** Moving away from general models toward personalized prediction
3. **Extended Prediction Horizons:** Research pushing from 10-30 min to 60-120 min windows
4. **Real-time Edge Deployment:** Optimized models for wearable devices and neural implants
5. **Explainable AI (XAI):** SHAP and attention visualization for clinical interpretability

### 9.2 6.2 Identified Research Gaps

Gap	Current State	Opportunity
Long-term prediction (>2 hr)	Few studies achieve >60 min	Ambulatory warning systems
Cross-patient generalization	Patient-specific models dominate	Transfer learning research
NeuroVista DL methods	Only 6 papers; mostly non-DL	Apply CNN-LSTM to 521-day data
Concept drift adaptation	Only 1-2 studies address	Continuous learning systems
Multi-modal fusion	Mostly EEG-only	ECG, EMG, accelerometer fusion
False positive burden	FPR 0.05-1.0/h still problematic	Patient quality of life impact
Prospective validation	Retrospective dominant	Clinical trial evidence needed
Multiday cycle prediction	NeuroVista shows promise	Extend Karoly's cycle forecasting

### 9.3 6.3 NeuroVista Research Gap Analysis

Despite being the **first FDA-approved implantable seizure prediction device trial**, NeuroVista has only 6 indexed papers:

### 9.3.1 Why NeuroVista is Underutilized

Factor	Impact
Data access restrictions	Not publicly available like CHB-MIT
Small sample size (n=15)	Limits statistical power for DL methods
Device-specific focus	Original papers focused on device, not algorithms
Geographic concentration	Melbourne-based research group dominates

### 9.3.2 Unique Research Opportunities

1. **Longest continuous recording:** 521 days mean vs CHB-MIT's 40 hours mean
2. **Multiday seizure cycles:** Karoly (2020) showed circadian + multi-day patterns
3. **Environmental factors:** Chen (2022) linked air pollution to seizure risk
4. **Seizure dynamics:** Schroeder (2022) discovered pathway duration relationship
5. **Real-world validation:** Ambulatory data vs hospital-controlled recordings

### 9.3.3 Recommended NeuroVista Research Directions

- Apply modern CNN-LSTM architectures to long-term iEEG data
- Develop multiday cycle-aware prediction models
- Study concept drift over months/years of recording
- Investigate environmental trigger integration

## 9.4 6.4 Recommendations for Future Research

1. **Address class imbalance systematically:** Standardize WGAN-GP or EEGAug approaches
2. **Standardize evaluation metrics:** Report sensitivity + FPR + prediction horizon consistently

3. **Explore concept drift:** EEG patterns change over time - adaptive models needed
4. **Multi-center validation:** Most studies use CHB-MIT; broader validation required
5. **Clinical deployment studies:** Bridge gap between research accuracy and clinical utility

## 10 7. Conclusion

This literature review demonstrates the CrossRef Local MCP Server's capability to rapidly search and retrieve relevant academic papers (167M+ indexed works). Key findings:

### 10.1 7.1 Seizure Prediction State-of-the-Art

- **Best performance:** CNN-LSTM hybrid with attention achieves  $\sim 97\%$  sensitivity, FPR  $\sim 0.05/h$
- **Standard prediction horizon:** 10-30 minutes, with emerging 2-hour predictions
- **Critical metrics:** Sensitivity and FPR together indicate clinical utility
- **Dominant database:** CHB-MIT (23 patients, 916 hours) used in most studies

### 10.2 7.2 NeuroVista Findings

- **6 papers found** using simplified "neurovista" query (vs 0 with compound queries)
- **Unique dataset:** 15 patients, 521 days mean recording, 3,789 total seizures
- **Key insight:** Multiday seizure cycles (Karoly 2020) enable novel forecasting
- **Gap:** Modern DL methods (CNN-LSTM) not yet applied to this long-term data

### 10.3 7.3 Search Strategy Lesson

FTS5 compound queries may fail silently; **simple single-term queries** are more reliable for named datasets.

Generated via CrossRef Local Remote MCP Server Database:  
167,008,748 papers | 1,788,599,072 citations Search speed: 100-  
400ms per query (2.83ms for "neurovista")