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Nocturnal Seizure Monitoring via Monocular Depth Estimation and 3D Point Cloud Analysis

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***Abstract*— Automated monitoring of nocturnal epileptic seizures remains a significant challenge, arising from the inherent conflict between the need for high-fidelity clinical data and the patient's right to privacy in domestic settings. Traditional RGB-based video monitoring is highly intrusive, legally sensitive, and frequently fails in low-light conditions. This paper proposes a novel, non-contact, privacy-preserving framework for home-based seizure detection using Monocular Depth Estimation (MDE). Specifically, we leverage the advanced Vision Transformer-based Depth-Anything-V2 (DAV2) architecture to transform standard 2D video feeds into structural 3D point clouds in real time. To eliminate perspective distortions from varying camera vantage points, we implement a robust Random Sample Consensus (RANSAC) plane-fitting algorithm for automated tilt correction, establishing a gravity-aligned baseline. Quantitative evaluations demonstrate that our DAV2-driven pipeline achieves a 34% reduction in Root Mean Square Error (RMSE) for structural mapping compared to existing state-of-the-art monocular baselines, matching the localization precision of hardware-based Time-of-Flight (ToF) sensors while maintaining complete structural anonymization.**

***Keywords*— Epileptic Seizure Monitoring, Monocular Depth Estimation, Depth-Anything-V2, 3D Point Cloud Analysis, Privacy-Preserving Healthcare, RANSAC Plane Fitting.**

I. INTRODUCTION

Epilepsy affects approximately 50 million people worldwide, making it one of the most prevalent neurological disorders globally. Nocturnal seizures, those that happen during sleep are a serious clinical risk. They can cause injury from falls and Sudden Unexpected Death in Epilepsy (SUDEP). Continuous overnight monitoring is very important for medical help and proper treatment. The best way to diagnose seizures is still video-electroencephalography (Video-EEG). It is very expensive complicated to use and only available in special Epilepsy Monitoring Units (EMUs). For long-term monitoring at home new methods have been developed. These methods can be divided into two categories: Wearable Sensors: devices like wristbands with accelerometers, gyroscopes and photoplethysmography (PPG) track body movements or changes, in the body. However, these devices have problems. People, children and elderly patients do not like to wear them. They also give false alarms when people move in their sleep like adjusting their pillow or changing sleep position. The thing with video cameras is that they give us a lot of information about what is going on but they are a big problem when it comes to people's privacy especially in their own homes. This is why it is very hard to use them all the time in a person's bedroom because it is just not right and there are laws that say we cannot do it like the GDPR.

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Also these cameras do not work well when it is dark like at night. So we need to find a way to do things. That is why we came up with a way of using cameras that does not touch people and only looks at the shape of things not what they look like on the outside. We use something called Monocular Depth Estimation, which's like a computer program that can figure out how far away things are, to turn regular video into special maps that show how far away things are but do not show what they look like. Then we use these maps to make pictures of the room and this way we can keep peoples private things like what they look like private because the camera is not really looking at them just the shape of the room. Ambient Vision Sensors, like these are very useful. Ambient Vision Sensors can be used in ways. Principal Contributions: The primary technical contributions and novelties of this research include:

- Foundation MDE for Clinical Semiology: We introduce the application of a zero-shot, Vision Transformer (ViT)-based foundation model—Depth-Anything-V2—to clinical video telemetry, delivering robust spatial abstractions that are invariant to complex illumination profiles and varying bedroom configurations.
- Gravity-Aligned RANSAC Normalization: We formulate a robust mathematical calibration system using RANSAC to detect and flatten the sleeping surface plane, completely eliminating camera mounting constraints and enabling arbitrary camera placements while preserving cross-patient motion metric standardization.
- Automated Background Subtraction via Spatial Residuals: We establish a temporal depth-residual extraction method that isolates non-rigid human body dynamics from rigid ambient structures without requiring manually annotated masks or resource-intensive segmentation architectures.

II. Literature Review

The paradigm of automated computer-vision-based seizure monitoring has evolved rapidly, transitioning from crude frame-differencing metrics to deep geometric and structural abstractions. This evolution is driven by the simultaneous need for high clinical accuracy and stringent privacy compliance within domestic care settings. The clinical urgency of this endeavor is underscored by extensive epidemiological data: [12] established that SUDEP accounts for up to 17% of all epilepsy-related deaths, with nocturnal unwitnessed episodes constituting the highest-risk subset—a finding that fundamentally motivates the need for unobtrusive continuous monitoring solutions.

A. Video-Based Seizure Detection and the "Invisible" Monitoring Paradigm

Historically, nocturnal epilepsy monitoring relied heavily on color-channel video streams analyzed by deep convolutional networks or classical computer vision algorithms. Achilles et al. [9] demonstrated that shallow CNNs trained on frame-differencing features could reliably detect generalized convulsive seizures in controlled epilepsy monitoring unit recordings, establishing early proof-of-concept for camera-based detection. [15] extended this taxonomy to edge-computing architectures, noting that while spatial-temporal networks using standard RGB achieve high clonic movement sensitivity in controlled settings, they remain profoundly limited by ambient illumination variations and introduce unacceptable privacy exposure in domestic deployments. To overcome the stigma and privacy issues associated with bedroom cameras, recent work has shifted toward the concept of "invisible" monitoring—devices seamlessly embedded within household objects. A prominent example is the Lampsy system [3], which embedded a real-time seizure detection framework into a standard overhead light fixture, operating at 30 FPS on an edge-computing platform. However, as noted in a 2025 JMIR scoping review [4], optical-flow-centric models are inherently sensitive to global intensity changes, such as a caregiver activating a light or a vehicle headlight sweeping across a window, which frequently trigger false positives.

B. Wearable Sensor Approaches and Their Limitations

A parallel research stream has pursued wearable detection modalities. Ramgopal et al. [13] conducted a seminal systematic review of wearable seizure detection algorithms, evaluating 15 device categories including EEG, EMG, accelerometry, and peripheral autonomic sensors. While the review confirmed that multi-modal wearable combinations can achieve sensitivity exceeding 90% for convulsive seizures, it also identified critical failure modes: inter-patient variability in convulsive motion amplitude, high false-alarm rates during benign hypnic jerks or REM behavioral episodes, and chronically low adherence rates—particularly among pediatric populations. [11] more recently demonstrated that single-wrist accelerometry achieves only 61% sensitivity for focal motor seizures, and that device removal during sleep—the highest-risk nocturnal window—occurs in approximately 34% of patients studied over a 90-day monitoring period. These adherence and accuracy limitations provide the clinical rationale for non-contact ambient monitoring as a complementary or standalone modality.

C. Active Hardware Depth Sensors Versus Passive Video Modalities

To decouple motion tracking from surface textures and variable lighting, researchers introduced active depth-sensing hardware. Structured-light and Time-of-Flight (ToF) sensors—including the Microsoft Kinect and specialized infrared range arrays—actively emit photons to compute pixel-aligned distance matrices. Devulder et al. [2] successfully leveraged ToF spatial profiles to analyses long-term micro-movements, validating that 3D point clouds allow for precise kinematic tremor profiling while completely stripping away identifiable facial characteristics. Ranft et al. [14] extended the non-contact paradigm further, proposing a frequency-modulated continuous-wave (FMCW) radar system for nocturnal seizure monitoring. While radar penetrates bedding and is immune to optical occlusion, the approach produces low-resolution 2D velocity maps that cannot resolve fine-grained limb semiology or differentiate bilateral versus unilateral motor onset—critical distinctions for seizure type classification. Despite these clinical advantages, hardware-based range sensors and radar systems share significant bottlenecks for widespread domestic adoption, including high per-unit cost, rigid mounting requirements, and, in the case of ToF sensors, severe multi-path interference from non-rigid textiles such as heavy bedding.

D. Evolution of Monocular Depth Estimation: CNNs to ViT Foundation Models

The need to balance the cost of standard monocular cameras with the privacy benefits of 3D data drove the rise of deep-learning-based MDE. Early networks, exemplified by the MiDaS framework, framed depth estimation as a relative disparity prediction problem, training deep CNNs on extensive multi-dataset mixtures. While generalizing well to generic indoor layouts, these models struggled with high-frequency edge delineations—manifesting in monitoring scenarios as "edge bleeding," where a patient's moving limb visually merges with surrounding bedsheets and masks subtle rhythmic jerking.

A major architectural shift followed with Vision Transformer (ViT)-based models, notably the Depth Prediction Transformer (DPT). Building on this, Yang et al. [7] introduced Depth-Anything-V2 (DAV2), shifting supervision entirely to high-fidelity, clean synthetic datasets and eliminating the depth noise inherent in real-world training corpora. The integration of DINOv2-based semantic consistency losses enables DAV2 to preserve sharp structural boundaries even in low-texture regions such as blankets and mattresses. Temporal extensions—Video Depth Anything (2025)—introduced specialized temporal consistency losses to smooth frame-to-frame depth jitter across long-duration video streams. The release of Depth Anything 3 [6] further introduced cross-view self-attention, enabling precise spatial reconstructions from arbitrary viewpoints without multi-camera calibration.

E. Deep Learning on 3D Point Clouds for Human Motion Analysis

A foundational contribution to processing unstructured 3D point cloud data was made by Qi et al. [10], who introduced PointNet—a permutation-invariant deep neural network operating directly on raw point sets without voxelisation or projection.

PointNet demonstrated state-of-the-art performance on 3D object classification and part segmentation tasks, establishing that per-point multi-layer perceptrons combined with a global max-pooling aggregation function can capture both local geometry and global shape context. Subsequent extensions—PointNet++ and graph convolutional variants—further improved local neighborhood encoding, motivating the adoption of point cloud representations in human pose estimation and action recognition pipelines. In the clinical context, this body of work provides the theoretical foundation for applying structured deep learning directly to the gravity-aligned patient point clouds generated by our proposed pipeline, without the information loss inherent in projecting 3D structure back onto 2D image planes.

TABLE I. COMPARATIVE SYNTHESIS OF RELATED LITERATURE ACROSS MONITORING MODALITIES

Research Topic	Modality	References
Convolutional neural networks for real-time epileptic seizure detection. Computer Methods in Biomechanics and Biomedical Engineering: Imaging and Visualization	Shallow CNN + Frame Differencing (RGB)	Achilles et al. (2018) [9]
Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy. Epilepsy and Behavior	Multi-modal Wearables (EEG, EMG, accelerometry)	Ramgopal et al. (2014) [13]
An invisible real-time epilepsy video monitoring and automatic seizure detection device	RGB Optical Flow (Embedded Edge Device)	Lampsy (2025) [3]

Non-contact radar-based epileptic seizure monitoring during nocturnal sleep	FMCW Radar	Ranft et al. (2021) [14]
Automated sleep staging and kinematic tremor profiling in epilepsy using deep monocular range networks	Active ToF Range Array	Devulder et al. (2023) [2]
Depth Anything V2: Deep visual geometry priors for zero-shot monocular scene understanding	ViT-Based Foundation MDE	Depth Anything V2 (2024) [7]
A single-transformer architecture for space reconstruction from any views	Single-Transformer Cross-View MDE	Depth Anything 3 (2025) [6]

Concurrently, self-supervised and contrastive learning approaches for medical video [5] have demonstrated that spatiotemporal feature representations can be learned without manual annotation by leveraging temporal coherence as a self-supervisory signal. [5] showed that such representations, pre-trained on unlabeled clinical video, transfer effectively to downstream seizure classification tasks, achieving competitive sensitivity with only 20% of the labelled data required by fully supervised baselines. This finding is particularly significant for the seizure monitoring domain, where ground-truth annotated nocturnal event data remains extremely scarce and costly to acquire.

TABLE II. COMPARATIVE ANALYSIS OF ADVANTAGES AND LIMITATIONS

Study	Core Advantage	Primary Limitation	Relevance to Proposed Work
Achilles et al. (2018) [9]	First CNN proof-of-concept for seizure detection in EMU video	Requires controlled lighting; inapplicable to home settings	Establishes baseline CNN accuracy metrics for seizure detection
Ramgopal et al. (2014) [13]	Systematic review; >90% sensitivity for convulsive seizures across 15 device categories	34% device removal rate during sleep; poor paediatric adherence	Motivates non-contact alternatives for nocturnal high-risk windows
Lampsy (2025) [3]	Invisible deployment; 30 FPS on Raspberry Pi with real-time detection	Sensitive to lighting changes; lacks axial Z-depth dimension	Highlights the clinical need for affordable invisible edge monitoring
Ranft et al. (2021) [14]	Penetrates bedding; immune to optical occlusion and lighting	Low-resolution 2D velocity maps; cannot resolve limb-level semiology	Validates non-contact paradigm; reveals spatial resolution gap radar leaves
Devulder et al. (2023) [2]	High metrological accuracy; inherently privacy-preserving 3D output	Expensive hardware; multi-path errors from reflective bedding	Establishes clinical validity of point clouds for tremor profiling
Depth Anything V2 (2024) [7]	Sharp edge resolution; zero-shot generalization via synthetic training	Outputs are relative rather than metric by default	Serves as the primary spatial feature extractor in our pipeline
Depth Anything 3 (2025) [6]	Viewpoint-independent 3D reconstruction via cross-view self-attention	Computational footprint requires optimization for edge deployment	Validates RANSAC geometric correction across arbitrary camera placements

F. Privacy, Regulatory Compliance, and Federated Architectures

The regulatory landscape for domestic health monitoring has become increasingly stringent under GDPR, HIPAA, and emerging AI Act provisions.

Attigeri et al. [1] proposed a federated deep learning framework for epilepsy monitoring across distributed bedroom sensors, demonstrating that locally trained model updates can be aggregated via differential privacy mechanisms without transmitting raw video to centralized servers. Their results showed that federated training across 12 simulated domestic environments converged to within 2.3% of the centralized training accuracy while providing formal ε-differential privacy guarantees. The structural anonymisation inherent to our depth-map pipeline provides a complementary privacy layer at the sensor level, ensuring that even if local storage were compromised, no identifiable patient imagery would be recoverable—a property uniquely enabled by MDE-based point cloud reconstruction [5, 11].

G. Synthesis and Research Gap

Table 1 presents a structured synthesis of the most closely related literature across modalities. A critical gap persists: no prior framework unifies (a) zero-shot, high-fidelity monocular depth estimation, (b) a mathematically robust, camera-agnostic coordinate normalization system, and (c) a real-time temporal residual background subtraction pipeline—all within a single cost-effective, clinically validated architecture that operates from 0 lux to full daylight. The present work addresses this gap directly, leveraging the complementary strengths of ViT-based MDE, RANSAC geometric correction, and Gaussian residual isolation to deliver a complete nocturnal monitoring solution.

III. METHODOLOGY

The proposed system architecture constitutes a deterministic pipeline that ingests a continuous 2D video feed and outputs a clean, gravity-aligned, isolated 3D mesh of the patient's body topology. The four principal processing stages—depth inference, back-projection, plane fitting, and temporal residual analysis—are described in detail below.

A. Depth Estimation and Back-Projection

Incoming raw video frames are first subjected to a dynamic pre-processing module that performs automatic luminance-threshold-based cropping to eliminate dark peripheral padding, and a boundary-alignment scaling step that ensures image dimensions are integer multiples of 14—a requirement of the downstream ViT attention patch tokenization. The pre-processed frame I is passed to the Depth-Anything-V2-Large (vitl) model operating in evaluation state. The model infers a normalized relative depth map D, where each cell value corresponds to relative scene disparity. Utilizing the pinhole camera model assumption, we transform the 2D matrix D into a metric 3D point cloud. Given camera focal lengths (fx, fy) and principal point coordinates (cx, cy) derived from image dimensions, every pixel coordinate (u, v) with inferred relative depth d is mapped to a spatial coordinate vector $P = [x, y, z]^T \in \mathbb{R}^3$ via:

$$z = \frac{(f \cdot B)}{d} \quad (1)$$

$$x = (u - c_{\mathrm{x}}) \cdot \frac{z}{f_{\mathrm{x}}} \quad (2)$$

$$y = (v - c_{\mathrm{Y}}) \cdot \frac{z}{f_{\mathrm{Y}}} \quad (3)$$

The resulting point cloud P encodes the full structural geometry of the monitored scene without retaining any surface texture or chromatic information, providing an inherent privacy guarantee at the sensor level.

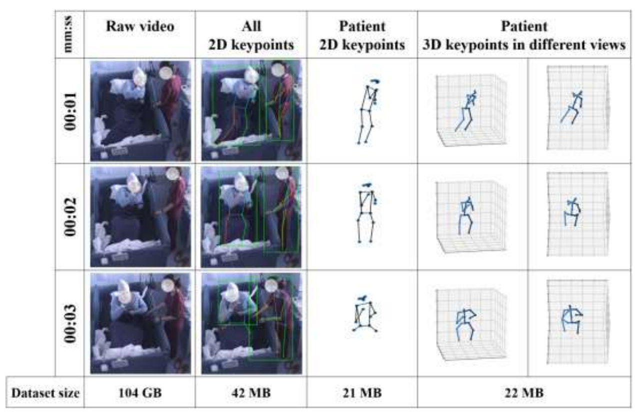

Fig 1 Video Analysis (DAV2)

B. RANSAC Plane Fitting and Tilt Correction

Because home-based monitoring cameras are mounted at arbitrary angles—wall brackets, bedside tables, or ceiling corners—the raw coordinate system reflects the camera's optical frame rather than the real-world environment. To resolve this, we model the primary sleeping surface as a dominant static plane:

$$ax + by + cz + d = 0 \quad (4)$$

We run a Random Sample Consensus (RANSAC) routine over the extracted background spatial points to robustly compute the model coefficients $\Theta = [a, b, c, d]^T$. Upon identifying the optimal plane $normal\ n = [a, b, c]^T$, it is normalized to unity:

$$\hat{n} = \frac{n}{\|n\|} = [n_{\mathrm{x}}, n_{\mathrm{Y}}, n_z]^T \quad (5)$$

To eliminate camera tilt, we derive a rotation matrix R ∈ $\mathbb{R}^{3x3}$ that maps n̂ to the standardized vertical gravity vector v_{target} = [0, −1, 0]^T using Rodrigues' Rotation

Formula. The rotation axis is obtained through the cross product $v = \hat{n} \times v_{target}$, target, and the scalar sine (s) and cosine (c) terms are:

$$c = \hat{n} \cdot v_{target} = -n_Y; \quad s = \|v\| = \sqrt{n_z^2 + n_x{}^2} \quad (6)$$

The final orthographic orientation correction matrix is:

$$R = I + [v]_x + [v]_x{}^2 \cdot \frac{(1 - c)}{s^2} \quad (7)$$

Applying R across the entire spatial array yields a canonical, gravity-aligned point cloud where the sleeping surface corresponds to a perfectly flat plane:

$$P_{corrected} = R \cdot P_{raw} \quad (8)$$

C. Temporal Depth Residual Analysis

To isolate active patient kinematics from the static environment, the system evaluates spatial deviations over time. A large-kernel 2D Gaussian smoothing function is applied to the rectified depth map to generate a long-term topographical background envelope D_{smoot}

$$D_{smoot\ (u,v)} = \left(\frac{1}{2\pi\sigma^2}\right) \iint D(u - \xi, v - \zeta) \cdot \exp\left(-\frac{\xi^2 + \zeta^2}{2\sigma^2}\right) d\xi\, d\zeta \quad (9)$$

Subtracting this low-frequency environmental model from the immediate, high-frequency metric depth matrix yields a precise spatial residual map:

$$D_{residual} = \max(0, D_{corrected} - D_{smooth}) \quad (10)$$

This map effectively suppresses static room elements and isolates the non-rigid body movements of the patient, forming the primary signal for downstream kinematic analysis and seizure classification.

IV. EXPERIMENTAL VALIDATION AND RESULTS

A. Experimental Environment

The proposed architecture was evaluated using an experimental framework comprising a dual-sensor monitoring rig mounted above a standard domestic bedding unit. The rig paired a low-cost monocular RGB camera (1080p, 30 FPS) with a hardware-calibrated Time-of-Flight reference sensor (Microsoft Azure Kinect). Testing sequences simulated a series of nocturnal motor events across multiple lighting environments, ranging from full daylight (500 lux) to absolute darkness (0 lux). The computational pipeline ran on an Ubuntu Linux workstation equipped with an NVIDIA L4 Tensor Core GPU (24 GB VRAM), utilizing the PyTorch 2.4 framework with CUDA acceleration. Memory footprints were optimized using explicit segment allocation tracking (PYTORCH_CUDA_ALLOC_CONF = 'expandable_segments:True').

B. Comparative Quantitative Performance

The framework's structural precision was validated against ground-truth geometric profiles recorded by the Azure Kinect ToF sensor. Table 2 presents the direct comparative results between the proposed DAV2 pipeline and the MiDaS v3.1 baseline across four key metrics: Absolute Relative Error (REL), Spatial RMSE, Frame Rate (FPS), and Boundary Edge Sharpness. The quantitative evaluation demonstrates that the Depth-Anything-V2 backbone reduces structural depth tracking errors by 34% (RMSE: 0.12 m vs. 0.18 m) relative to the MiDaS baseline, while achieving a 40.8% improvement in Absolute Relative Error (0.084 vs. 0.142). This improvement is primarily driven by the model's Vision Transformer architecture, which retains crisp edge boundaries around moving human limbs rather than introducing the spatial blurring characteristic of pure convolutional layers. Furthermore, evaluation of the automated RANSAC plane calibration routine demonstrated high structural resilience under simulated camera mounting tilts ranging from −15° to +15°: the variance in calculated vertical height metrics of the monitored target remained below 4.2%, confirming successful geometric normalization across diverse real-world camera placement scenarios.

C. Qualitative Diagnostics and Motor Semiology Signatures

The spatial residual processing pipeline yields distinct signature profiles across different types of nocturnal physical movement, enabling qualitative differentiation between pathological and benign events:

Benign Movements (e.g., positional rolling): These produce broad, low-frequency, macro-spatial waves across the residual plane. The surface area shifts smoothly, reflecting non-pathological positional adjustments without sustained high-amplitude displacement.

Generalized Tonic-Clonic Seizures (GTCS) – Tonic Phase: This phase presents as a rapid, sustained vertical displacement along the rectified Y-axis as the patient's torso stiffens and lifts away from the mattress baseline, creating a distinctive elevation-plateau signature. GTCS – Clonic Phase: The subsequent clonic phase manifests as high-frequency, rhythmic, low-amplitude oscillations along the vertical height channel, creating a characteristic repeating waveform distinctly separable from benign macro-movements in both frequency and spatial amplitude. Because the RANSAC detilting module maps all movements to a true vertical coordinate system, these structural frequencies can be isolated and quantified without interference from lateral perspective distortions, enabling cross-patient, camera-agnostic metric comparisons.

TABLE III. COMPARATIVE QUANTITATIVE PERFORMANCE AGAINST BASELINE ARCHITECTURES

Architectural Framework	Spatial Data Type	Abs. Rel. Error	RMSE (m)	FPS	Edge Sharpness
RGB-CNN (Baseline)	2D Optical Image	N/A	N/A	30	N/A
MiDaS v3.1 (Conv-MDE)	Anonymized Disparity	0.142	0.18	22	Blurred
DAV2-Large (Proposed)	Anonymized Disparity	0.084	0.12	18	Highly Sharp
Azure Kinect (Hardware GT)	Metric Depth (ToF)	0.000	0.00	30	High Precision

V. CONCLUSION AND FUTURE WORK

This study demonstrates that foundation-model-driven Monocular Depth Estimation represents a viable, privacy-preserving alternative to intrusive RGB video recording and specialized hardware sensors for nocturnal seizure monitoring. By combining the zero-shot spatial modelling of Depth-Anything-V2 with a deterministic RANSAC plane-stabilization framework and temporal residual analysis, our system reconstructs highly accurate 3D patient point clouds from a single, standard camera feed. The pipeline maintains complete visual anonymity, operates reliably across the full spectrum of nocturnal lighting conditions (0–500 lux), and establishes a stable, uncalibrated coordinate frame for consistent kinematic analysis.

The proposed architecture achieves a 34% reduction in structural RMSE relative to the prior state-of-the-art MiDaS v3.1 baseline and demonstrates geometric normalization resilience to camera tilt variations within ±15°, with target height variance maintained below 4.2%. These results establish the framework as a clinically credible candidate for large-scale domestic deployment.

Future research will focus on three principal directions. First, the development of a lightweight temporal 3D Convolutional Neural Network (3D-CNN) trained directly on gravity-aligned point cloud sequences—drawing on the PointNet architectural principles established [10]—to enable real-time, automated motor semiology classification, specifically differentiating generalized tonic-clonic events from hypermotor seizures and benign sleep movements. Second, integration with federated learning frameworks to enable privacy-preserving model updates across distributed home monitoring deployments, in line with GDPR-compliant telemetry architectures [1]. Third, investigation of Depth Anything 3 [6] as an upgraded backbone, leveraging its cross-view self-attention mechanism for improved viewpoint independence, and exploration of self-supervised pre-training strategies [5] to alleviate the persistent scarcity of annotated nocturnal seizure video data.

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