# DeepEpil: Towards an Epileptologist-Friendly AI Enabled Seizure Classification Cloud System based on Deep Learning Analysis of 3D videos

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***Abstract*—Epilepsy is a major neurological disorder affecting approximately 1% of the world population, where seizure semiology is an essential tool for clinical evaluation of seizures. This includes qualitative visual inspection of videos from the seizures in epilepsy monitoring units by epileptologists. In order to support this clinical diagnosis process, promising deep learning-based systems were proposed. However, these indicate that video datasets of epileptic seizures are still rare and limited in size. In order to enable the full potential of AI systems for epileptic seizure diagnosis support and research, a novel collaborative development framework is proposed for a scalable DL-assisted clinical research and diagnosis support of epileptic seizures. The designed cloud-based approach integrates our deployed and tested NeuroKinect data acquisition pipeline into an MLOps framework to scale data set extension and analysis to a multi-clinical utilization. The proposed development framework incorporates an MLOps approach, to ensure convenient collaboration between clinicians and data scientists, providing continuous advantages to both user groups. It addresses methods for efficient utilization of HW, SW and human resources. In the future, the system is going to be expanded with several AI-based tools. Such as DL-based automated 3D motion capture (MoCap), 3D movement analysis support, quantitative seizure semiology analysis tools, video-based MOI and seizure classification.**

***Index Terms*—Clinical MLOps, Video based diagnosis support, Cloud computing, Clinical research support, Epilepsy, Seizure semiology**

## I. INTRODUCTION

Deep learning (DL) is a very promising technology for novel clinical diagnosis support tools in many medical challenges. We have been tackling one of these challenges for more than 20 years – the computer-aided epileptic seizure detection and recognition - and report here our recent efforts in the use of DL in such a challenge. Epilepsy is one of the major neurological diseases, affecting approximately 1% of the world population, with 30% of these cases being refractory epilepsy [1]. For clinical diagnosis and pre-surgery evaluation seizure semiology is an important tool. Nevertheless, during the assessment of seizures, epileptologists rely solely on qualitative visual inspection of seizure videos from the Epilepsy Monitoring Units (EMUs), utilizing movement of interests (MOIs) [2]–[5], that they add to the information (qualitative and quantitative) they obtain from electroencephalogram (EEG).

To the best of our knowledge, we have been collecting and quantitatively analysing the largest 2D+3D-video-EEG epileptic seizure database in the world using a previously reported system called NeuroKinect [6], [7]. This system continuously collects 2D+3D videos and multi-channel EEG of epileptic seizures from 3 beds at the University of Munich EMU. Along these 20 years of R&D approaches to this medical challenge – our first paper on the subject was published on IEEE Trans. Biomedical Engineering in 2002 [8] – this database has been providing novel insights on quantified seizure semiology [9], [10]. It is now intended to be significantly extended, richly labeled, analyzed and then utilized for DL based classification of MOIs and seizures, opening a new world of opportunities to pursue the initial objective – automatically detect and recognize different types of epileptic seizures.

Although, there are general labeling and Machine Learning (ML) analysis tools both running over programming platforms (such as Matlab) or available online, the specific requirements of this collaborative multi-disciplinary effort, detailed in section III, demands a special type of Machine Learning Operations Framework (MLOps) specifically designed for this purpose. The recent fast advance and increased complexity of ML/DL [11] applications development is demanding for a

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new type of “Development Operations” (DevOps) frameworks that are called MLOps [12]. These frameworks are a current trend in ML/AI and rely on a set of practices to iteratively develop, integrate and deploy ML models with incremental improvements into the production system with high software (SW) quality. It makes possible the early deployment of the production system, providing rapid feedback from the users and the possibility for early real world testing during development, which in a ML/DL research environment where models evolve iteratively and highly based on big-data availability is especially useful [13].

In this paper we present *DeepEpil*, a cloud-based, epileptologist-friendly MLOps framework intended to support an international clinical big-data AI-enabled epileptic seizure analysis effort based on 2D+3D video, following a feasibility study recently presented at the IEEE ICASSP conference by our group [14].

## II. RELATED WORK

As stated above, our research group has a long-standing experience in quantitative analysis of seizure semiology. Utilizing clinical motion capture (MoCap), to quantitatively analyze ictal seizure semiology, such as ictal head turning [9] and ictal upper limb automatisms [10], we found, for the first time, we can differentiate between seizure syndromes, and provide clear clinical localizing and lateralizing information. In order to improve robustness and precision of these classifications, we have demonstrated the advantage of using a 3D MoCap approach [15], with a multi-camera, expensive, but highly precise system. To make our approach more usable at the EMU hospital environments, we further implemented a portable, low-cost and markerless solution - called NeuroKinect – based on a Microsoft Kinect RGB-D camera that produces 3D videos and that proved to be more suitable for use in the clinical environment [16]. This system has been continuously acquiring 2D+3D video data from the epileptic seizures from 3 beds at the University of Munich EMU since 2015 [6], [7]. To manage this data the Neurokinect software ecosystem currently consists of the KiT (Kinect Tracker) application, to acquire, the KiMA (Kinect Motion Archiver), to edit, crop and organize data storage and KiSA (Kinect Seizure Analyser) to analyze the acquired data from the epileptic seizures [7]. These applications were developed with the intention to support one EMU at a time, moreover, the KiSA application carries the analysis through pipelines implemented in MatLab, which is an obstacle to convert it into the aimed cloud-based system.

This exact dataset has already been utilized for DL based epileptic seizure classification by our research group [17]. Similar alternative datasets were also explored for DL based classification as well, by our joint Munich-Porto research group [18], [19]. These approaches were addressing the limited size of the datasets by neglecting temporal features. In the literature, similar datasets were explored for video based epileptic seizures classification, with hierarchical DL classification approaches, dividing classification to parallel threads, or focusing on different parts of the body in several configurations [20]–[24]. These above mentioned approaches attributed performance limitations mainly related to the size of the datasets. These include, but not limited to, prone to overfit, utilizing subject specific features, imbalanced classes, high variability of features compared to the size of the dataset. In summary, all of these papers indicate a strong demand for richly labeled data in this domain.

To overcome these issues, we recently proposed an action recognition DL based approach employing transfer learning, which utilized the temporospatial features of the seizures, with very promising state-of-the-art results [14]. The proposed pipeline took advantage of I3D feature extraction, a 3D convolutional neural network (CNN) based action recognition architecture, by utilizing external data for low level feature extraction, thus using scarce clinical data only for high level training for clinical classification. This approach indicated the feasibility of the system, and mitigated the size limitations of the dataset. Although this research was conducted on just a part of the above-mentioned NeuroKinect database – used infrared videos from 126 seizures (33.5GB of data), it still pointed out the high demand for significantly more clinical data. Therefore, it is essential to develop a scalable framework to extend the Neurokinect dataset efficiently, by acquiring and richly labeling samples in collaboration with clinicians, to satisfy this demand. These triggered the need of an MLOps type of development framework for iterative ML models test&deploy we present here.

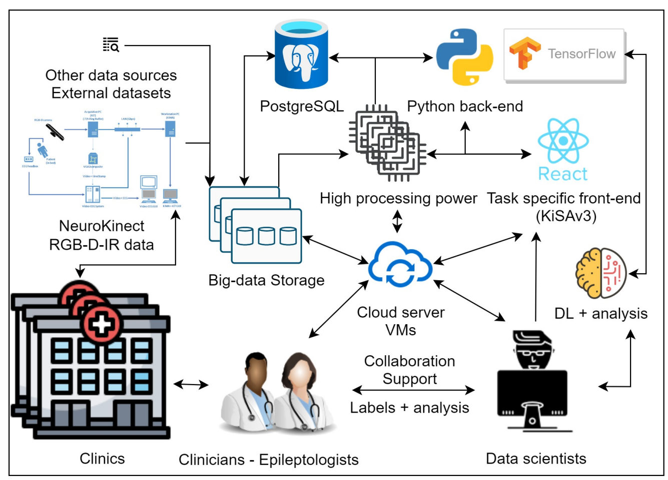



Fig. 1: Overview of *DeepEpil*, the designed high performance MLOps collaborative framework for developing a scalable DL assisted clinical research and diagnosis support system for epileptic seizures in the cloud, integrating NeuroKinect [7].

## III. METHODS

### A. Application environment

The process of data acquisition and utilization in this clinical domain face several specific challenges. Samples are highly dependent on the number of available suitable patients, clinicians and EMUs, where the acquisition is carried out.

These samples can not be collected anytime, as seizures appear randomly, thus the number of usable seizures can fluctuate and cannot be predicted. Practically, this continuous Neurokinect data stream creates raw data of 2TB per day and bed. From this only selected segments containing seizures are exported and stored for later analysis. Therefore they are scarce and have a highly limited availability for acquisition and labeling. As the data collection and preparation spans on a long period of time, it is beneficial to implement a continuous DevOps and MLOps approach, a set of practices to continuously develop and deploy the SW and ML models with high quality, to shorten the systems development life cycle and provide continuous delivery. This approach is advantageous both for the clinicians and ML/DL developers. The epileptologists are able to adopt and utilize the system in early stages of the development cycle and can be deeply involved into this process, providing crucial feedback to the developers. Moreover, in this case, the clinicians' workload related to data labeling and analysis is reduced and distributed, more aligned to their daily demanding clinical practice.

*1) Target dataset:* The target dataset is being acquired with the Neurokinect 3.0 system (Fig. 1) [6], [7]. This system is a three-bed Kinect v2 3Dvideo-EEG system developed for epileptic seizure monitoring, currently deployed at the EMU of the University of Munich, and under deployment at the EMU of the University of Porto. Kinect v2 acquires multiple streams of data namely, 1920x1080 HD-RGB, 512x424 infrared (IR) and depth videos, with a sampling rate of 30 fps. These data streams are stored in our proprietary format. The currently existing raw dataset has a size of 2.1 TB, consisting of more than 500 epileptic seizures from more than 100 patients. These seizure samples have a size of 1GB to 20GB with an average size of more than 4GB per sample.

Therefore during the system design the exceptionally large size of the samples and the sensitive nature of clinical data had to be thoroughly considered.

*2) Target users and utilization:* Two main user groups are using the system in a collaborative setting (Fig. 1). The first group are the clinicians. These epileptologists are located in several clinics and countries, where the local Neurokinect systems are deployed and data is acquired. These users are responsible to provide the clinical labels for the epileptic seizures video data. These labels include, relevant patient and clinical data, classifications and time stamps of the seizures and MOIs. In the future, these are going to be extended to movement tracking and quantitative analysis of the seizures as well.

The acquired data combined with the labels are utilised by the second user group. The data scientists develop ML approaches to classify and quantitatively analyse these seizures and MOIs. The designed methods are integrated continuously into this system. Moreover, the system is continuously developed and improved for smooth collaboration with the clinics, including new features requested by the clinicians, or suggested by the developers, to provide valuable support for epilepsy research and diagnosis in the future.

In this proposed collaborative setting the users iteratively utilize big data both for clinical research and ML research. Therefore, both user groups are mutually benefiting from the proposed system, already during the development phase.

*3) Framework design - considerations and requirements:* The overview of the proposed framework of the collaborative cloud based system is presented on Fig. 1.

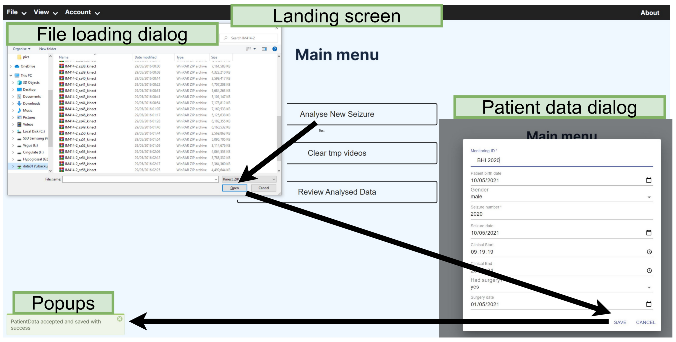
In order to efficiently utilize the already rather large target dataset (sec. III-A1) - which is continuously growing with time and number of adopting EMUs - it is essential to minimize data transfer on low throughput connections. Therefore, to manage and process the dataset, it is advantageous to utilize a centralized, scalable storage and server, as commonly adopted in big data processing environments. The clinical data is sensitive by is medical nature, therefore it is essential to ensure restricted and privacy enforced access to it, following the current EU GDPR [25]. For this reason, it is required that only authorised users can access the server and system through an encrypted VPN connection from remote locations. Furthermore, no patient name or other identification information is stored and only a generated identifier code is used. The patient identification is only known by the epileptologists that are involved in the patient treatment and stored in the EMU.

Considering the clinician user base (sec. III-A2), it is expected that the system is easy to access, essentially providing a plug&play approach, user friendly, and process the data rapidly. In order to fulfill these requirements setting up the environment on a scalable virtual machine (VM) is favorable. This solution provides the clinicians with an easy to access, secure, high performance environment, without any complicated setup requirements. Therefore, independently from the HW resources of the clinics and clinicians, who usually have access to personal computers and laptops, the developers are able to ensure and maintain a high performance HW and SW environment scaled to the demand. Moreover, the developers are able to conveniently provide real-time remote support anytime for the clinicians.

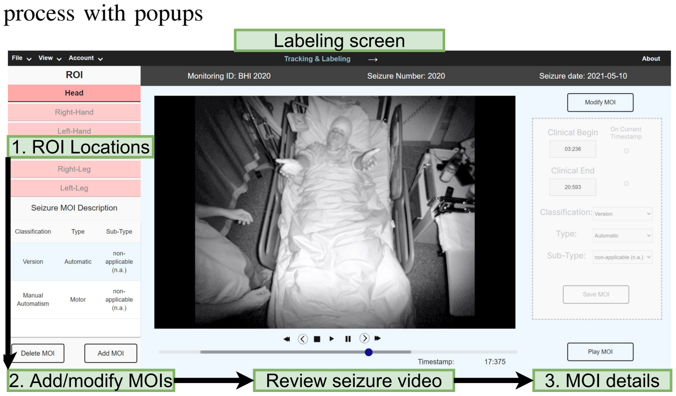
Given the two user base have very distinct utilization goals of the system, both use cases have their specific requirements. The clinicians require an easy to use GUI front-end (sec. III-B) for the labeling and analysis of the seizure videos. While the data scientists, require a high throughput, flexible access to the organized dataset from the back-end (sec. III-C), with scalable computational resources, such as CPUs and a GPU cluster. In detail, this require the dataset stored on the central server, where it is processed. It maximizes performance, by minimizing large file transfers, as ML training requires frequent access to the whole dataset. Moreover, the VM is deployed on the same server, thus the clinicians have also rapid access to the data. These two types of HW setups are configured on a central high performance server. Where, if required, more VMs can be deployed or HW resources conveniently scaled up.

### *B. Front-end*

The front-end (Fig. 2) was developed in React to provide a user friendly GUI for the clinicians. This web based GUI is




(a) The landing screen allows the user to load our proprietary data from the server for labeling and analysis, then it prompts the user to fill in relevant patient data, while providing feedback about the process with popups




(b) The labeling screen lets the user review the seizure video and add to each ROI the associated MOIs

Fig. 2: Showcase of the main features of the React front-end

conveniently extendable to incorporate upcoming features to the system. Moreover, a web based GUI was chosen to allow future upscale of the system to more users and clinics.

The landing screen (Fig. 2a) consist of the main menu, where the user is able to initiate new seizure loading and labeling or continue with a previous one. The video data files can be accessed from the data storage on the server. After a new seizure file is chosen the data is loaded and the user is notified with a popup of the state of the loading, then prompted with a dialog to fill in relevant patient data.

The labeling screen (Fig. 2b) allows the clinician to review the video, and to add and modify the MOI classifications with their corresponding start and end time (timestamp), associated to each region of interest (ROI). The interface has a menu-strip on the top on each screen for easy navigation, and to access relevant functionalities onscreen.

The front-end is designed to guide the workflow of the clinicians and provide continuous feedback to the users, for example in the form of pop ups.

### C. Back-end

The back-end is based in Python, this high level open source programming language is the favorable option to satisfy all requirements (sec. III-A). As it is widely utilized in the data science community, it ensures compatibility with common ML and data science libraries, such as Tensorflow, Keras, PyTorch and other data processing, analysis tools. It loads and manipulates data, in our proprietary format, on the server to minimize large data transfers. Only compressed video data is streamed to the front-end, while keeping raw data available for processing.

To establish connection with the front-end the Python back-end runs a flask app, which accepts and sends the http requests from the React front-end. For structured storage of labels and relevant clinical data a PostgreSQL database is managed from the Python back-end with SQLalchemy ORM (Fig. 3). Considering the goal of ML training managing the database from Python thorough an ORM is required for effective code utilization, as the developed functions for data management associated with the labeling can be re-utilized for the ML training and vica-versa.

The PostgreSQL DB has hybrid organization to optimize run time. It stores lightweight data, such as labels, user information and only maps the seizure video data from the big data storage. Utilizing a relational database is also beneficial to prepare the system for multiple users, associated with multi premises and clinics.

In summary, this SW organization seamlessly fits into the proposed MLOps ecosystem.

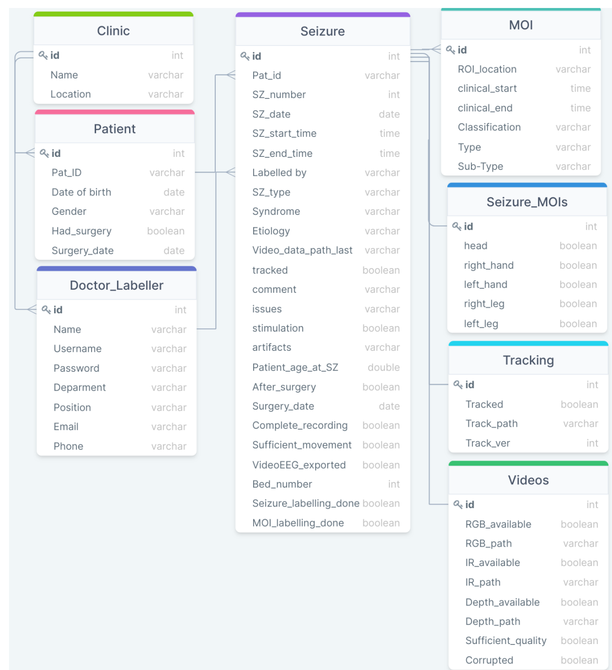



Fig. 3: The PostgreSQL database architecture, containing seizure and MOI labels, users, relevant clinical and patients information

## IV. RESULTS

In this work, a collaborative framework between epileptologists and ML researchers is presented for video based epileptic seizure analysis. During the framework design it was essential to develop a collaborative system suitable both to clinicians and researchers, with MLOps in mind. The system was prepared to develop state-of-the-art research on DL based applications for clinical research and diagnosis support. In order to disseminate the system and promote adaptation in new clinics and to satisfy the DL data demands the system is appropriately scalable.

The significance of this contribution is this framework is the foundation of both clinical epileptic seizure semiology based classification research and also AI research for this clinical challenge. It includes 3D MoCap development for a heavily occluded clinical scenario, then employ an action recognition approach to classify automatically MOIs and seizures from the 3D MoCap. Utilizing the attention of the networks, the significant contributing factors to the classifications can be explained and visualized to the doctors. This is crucial to build trust for utilizing such a system in clinical practice. Moreover, it might uncover new clinical signs. The proposed development will allow the clinicians to accurately modify the suggested 3D MoCap tracings and classifications, thus receiving a more accurate quantitative 3D movement analysis, while improving the target labels for the DL frameworks. This approach has the advantage of speeding up clinical research, while ensuring a symbiotic learning for the DL subsystems, essentially producing a clinical knowledge transfer and enhancement.

## V. CONCLUSION & FUTURE WORK

In conclusion, this paper presented a novel cloud based, high performance collaborative framework for developing a scalable DL assisted clinical research and diagnosis support system for automated detection and classification of epileptic seizures. The developed framework incorporates an MLOps approach, to ensure efficient collaboration between clinicians and data scientists. This framework will be key to iteratively develop novel DL-based automated 3D motion capture (MoCap) for quantitative seizure semiology analysis, following the feasibility study results published recently by our R&D group [14].

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