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RESEARCH ARTICLE

Construction of a Social-Media Based Clinical Database–Roadmap, Challenges, and Feasibility for ADHD Recognition

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ABSTRACT The shortage of available high-quality clinical databases restricts medical diagnostics downstream. Clinical databases are often limited to controlled non-natural environments, they are restricted due to privacy limitations and require complex scoring procedures that ultimately result in rater bias. Social media includes massive amounts of information on subjects through streams of text, audio, and video data that are accessible and currently underutilized for medical research. In this work we propose a method for utilizing this information by constructing databases for medical condition assessment. To this end we have created SMDC (Social Medical Data Constructor), a utility based on medical expert requirements. Data Features and non-confidential demographic information are extracted online, and labels are derived using data mining techniques. We examine the feasibility of the suggested technology with ADHD recognition from a database extracted from YouTube clips using the self-tagging as ADHD labels. The database maintains privacy and copy write limitations, and no personally identifying information is collected. To validate the database, we show a high correlation of the derived model's predictions with expert labeling (r = 0.68) and compatibility of six known ADHD motor biomarker features of hyperactivity to the ones derived using our database. Furthermore, we extracted from the video clips kinematics features and reached ADHD recognition accuracy of 83%, and 81%, for female sand males respectively. The suggested technology has the potential to assess natural real-life behavioral properties of the medical condition, and may further be of use as a pre-training phase allowing fine tuning on actual clinical data with minimal data requirements.

INDEX TERMS Machine learning, databases, social networks, medical diagnosis, ADHD.

I. INTRODUCTION

Guaranteeing sufficient clinical datasets pertaining to various clinical conditions is essential, as the lack of sufficient databases can adversely affect research advances. The quality of databases can affect the way databases represent real-world conditions and diversity [1]. For example, some existing clinical databases are collected in non-natural environments, and thus do not always reflect the subject medical condition [2].

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In addition, collecting clinical datasets is a cumbersome process, typically requiring input from medical professionals, and can suffer from rater bias, and subjectivity [3]. Privacy limitations limit the wide use of datasets for many research domains, as is the case for instance with the use of video recordings exposing individual Parkinson Disease (PD) patients [4].

Video audio and text are informative data that can be used as behavior capturing tools and produce behavioral markers for medical condition assessment [5]. Automatic analysis of video recordings in the clinic can provide information about severity of disease such as PD and dementia. Vocal recording can be used for early detection of Parkinson's disease, extract subjects' mood, psychological profiling, and medical condition [6]. Text mining can also be used to extract medical conditions such as cognition decline. Yet, the recordings in the clinic are limited, and biased, and still require the patient travel time, and medical staff time. This brings the need to exploit this information into clinics at natural or home environment settings.

Social media (SM) information can help provide continuous assessment of behavior and interaction type that can assist in psychological and medical condition assessment [7]. One advantage of using SM data is the ubiquity of data found in social networks. SM products like multimedia, reflect daily life experience, with less clinical bias as it is usually in natural home settings conditions [8]. Thus, it promises to be used in continuous treaeffortto evaluate treatment efficiency, and continuous optimizing drug dose with minimal clinical assistance and efforts. To benefit from the SM, there are many challenges like extracting the data, to ensure its reliability, privacy, and accessibility.

SM includes massive amounts of information in text and video, that is currently not fully exploited for medical assessment. Some works have shown that SM can be used for marketing. In medical field automatic assessment of medical condition is still limited, as the information suffers from incorrect labeling, requirement to doublecheck the data, verify the data is real and not artificial (boot), and different formatting and recording conditions. In particular, there are no research to assist in common neurological diseases like Attention-Deficit/Hyperactivity Disorder (ADHD) and Autism Spectrum Disorder (ASD) where continuous monitoring at home environment are important for optimizing treatment plan [9].

Attention-deficit / hyperactivity disorder (ADHD) is the most common behavioral condition and the second most common chronic disorder in children [10]. The diagnostic criteria for ADHD have evolved over time, the assessment and tools for evaluation have remained essentially the same [11]. ADHD remains a largely clinical diagnosis. Current recommendations for diagnostic evaluation of possible ADHD include a comprehensive history of prenatal, perinatal, and family history; school performance; environmental factors; and a detailed physical examination [12].

Recently, automatic body and facial were shown to be used in ADHD diagnosis [13]. Body and face gestures can capture internal states and be used to characterize behavioral patterns that can be used in neurological disease diagnosis [14]. Body and facial features can be extracted by muscle activity with wearables [5], but recently with advances in computation, data storage, and mobility human activity profiling can be captured with radar [15], sonar [16], and optical technologies [17]. The most common method is video recording based on optical monitoring. The body and facial features can be assessed by using deep learning techniques [18]. To overcome the massive data, storage, and computation, we can use trained NN to extract lower dimension representation (embedding), like the body edges [19], skeleton key points [20] for the body and face, and facial Action Unit (AU) that capture the dynamics of the facial expression [21]. The most feasible and common one, with different trained models on millions of subjects is the subject landmarks of the skelton and the face. Video based analysis, requires massive data and calculations, and unlike wearables, is limited to home environment, suffer from shadowing or partial information, require massive data and computational resources, suffer from ambiguity. Difficulty in accurately and consistently measuring body movement: Body movement is influenced by a wide range of factors, such as age, sex, body size, and physical activity levels, which can make it challenging to obtain reliable and consistent data.

In this work, we map the challenges in building social media-based databases and define mechanisms to build such a database. We then demonstrate the principles and build a database of video clips for the ADHD use case, with demographic information, focusing without loss of generality, on the field of neurological diseases and disorders and behavioral database. For this, we tried to use available data from shared SM, and derive a video database for ADHD, based on self-tagging, and video content. We built a software utility that collects multi-media stream, demonstrated on collection of video clips from YouTube (google) with ADHD tagging and show mechanism to detect and remove artifactual video clips. To verify the labeling, based on self-tagging, we validate the data with a medical expert in the field, analysis the relation between the different label score approaches, and showed a mechanism to combine both when available. We then show that with a simple classifier using this database we can achieve over 82 percent accuracy with three different measures.

The work has fourfold contributions. First, the concept of construction of semi-clinical dataset from available SM, consisting of individuals with and without medical condition, can overcome the limited available clinical datasets. This approach is unique to handle privacy issues, IP overcome, and in the ways clinical knowledge; Second, we suggest a scheme and implement a software utility is user-friendly and include minimal manual tedious intervention like existing dataset collection procedures. Unlike traditional clinical datasets, the suggested SM based database is less limited in size, can be refine by the user easily, reflect real-life pathologies, and do not suffer from human rater bias; Third, the suggested database can include context like activity type and automatic artifact removal methods can be used to extract the context and hence can improve the classification accuracy; and Fourth, the suggested dataset do not replace traditional clinical datasets, but can be used in a hybrid approach for first level training (pre-training) before more verified fine tuning of clinical decision support system and hence has a

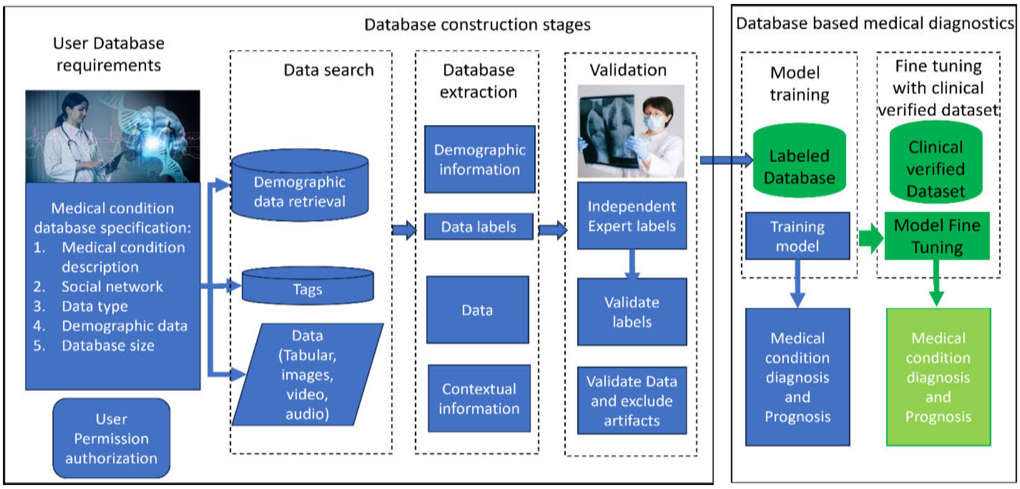

FIGURE 1. Data construction stages.

potential to reduce the dataset size requirements, and improve its generality and accuracy.

The paper starts with a description of the suggested medical database construction. In the third chapter we apply the suggested methods for the clinical case of ADHD with multimedia type of a video. In the fourth chapter we describe validation setup and test configuration. The fifth chapter describes the results, and the sixth chapter concludes the results and suggest direction for future work.

II. CLINICAL DATABASE CONSTRUCTION MECHANISM

A. DATA EXTRACTION

The clinical database extraction mechanism needs to collect the requirement related to the medical condition, population of interest, type of data and format, and social media type. The database requirement's structure includes medical condition of interest (disease, disorder, or pathology), media type (video, audio, text, images), the SM of interest (Twitter, Facebook, YouTube, etc.), the demographic information of interest (gender, age). Data type can be in the form of tabular data, audio, and video. The data is collected using the dedicated application and stored in the cloud in the application dedicated place. The user will be asked to direct to dedicated memory for storage. for the required database. Insufficient data space will give a user alert. An example of user definitions is shown in Figure 2.

Demographic data includes subject characterization and identification details like gender, age, location, economical condition and more [22]. We extract the demographic information from the metadata of the SM content or using automatic datamining utility from the retrieved data, we then manually added missing information and fixed the labels using the labeling extraction tool.

Database formatting and storage is a key issue in making the data accessible for different people. The data needs to be compatible with existing standards according to the methodology in the field [23]. Database type can be of any existing standard, like tabular data like comma separated file (CSV), images standards like Joint Photographic Experts Group (JPEG), and videos standards like MPEG. The subject's metadata and labels can be saved with CSV or JSON formats, storing columns such as ID, contextual data and link or path to the related data file.

B. LABEL AND CONTEXT EXTRACTION

To deploy Artificial Intelligence (AI), proper labeling of the data with related clinical score is required in medical research [24]. The label enable precision medicine approach and includes the disease name, and the scores of the different symptoms measured by clinicians, and sometimes, the medical description of an expert with a few clinical description sentences [25]. For our research, we used a labeling tool called "Label Studio" to create an app that allows professionals to label the data [26]. This approach allowed us to generate a dataset with more accurate and reliable labeling and ensure the quality and reliability of the dataset by cleaning and filtering based on various criteria, including the gender of the subjects, presence of noise and banners, and editing style.

In addition to the self-label, we can also extract context information from the media directly using data mining. This additional context, can be used for labeling, or sub-labeling of the data and assist in improving the prediction model accuracy [27]. For instance, the information about treatment type, drugs, on-off information, instance, the timing of usage, and activity type. To reduce ambiguity, and for better classification, accurate activity type recognition can assist in medical analysis in fields like and neurology and ADHD [28]. This can be performed using automatic context utility from the retrieved data.

C. DATASET QUALITY AND RELIABILITY

Dataset reliability is an important factor that influences medical diagnosis accuracy. The dataset reliability depends on the

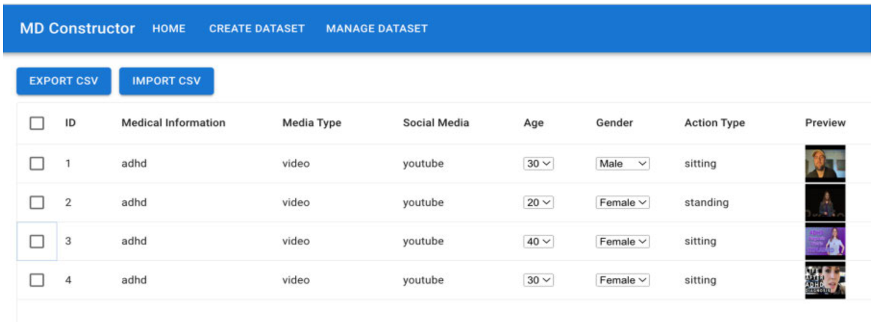

FIGURE 2. **Video extraction gui example for ADHD.**

data quality, and the related labeling and description of the data.

Data quality is affected by factors like poor image quality, if the signal mixed with other signals in multi-subject environment, on how clean the data is (existing artifacts), and adequate number of samples to ensure consistency of the data [29].

Data labeling include categorical scores and recently with using Large Language Models (LLM) can also include the data description used as upper dimensional labeling [30]. Inaccurate labeling and description can lead to prediction error of the model. For example, documenting the treatment timing and medication dose can change the symptoms of the medical condition [20]. In SM, there is usually no such documentation, and the data is not recorded in a controlled environment. In addition to lack of documentation of important details, there are many cases that the SM labeling is wrong, or biased. For instance, labeling based on self-scoring can include inherent bias due to the subjectivity of the report [1].

D. DATASET VALIDATION

For this, the database collection should be accurate, and be validated and corrected to remove data outliers and reduced label noise [31]. For SM based database we suggest the following means to mitigate over the bias inherent in self-reported data on social media platforms: 1) detect inherent abnormalities and inconsistency of the labels with other data textual description using LLM models; 2) perform auto-labeling based on the data content using data mining techniques and cross correlating with the labels to estimate the reliability of the labeling; 3) clinical verification of the labeling of representative portion of the data set; 4) use statistical analysis and machine learning algorithms that are tolerant to certain level of label noise, for example under assumption that symmetrical label errors average out with large enough data samples [32], [33].

E. ETHICAL CONSIDERATIONS AND SUBJECT PRIVACY

We need to ensure its compatibility with ethical and law regulations related to subject privacy, ensuring compliance with medical ethics standards and data protection regulations [34]. We focus on this study, without loss of generality, on publicly available SM. Still, to protect the subject the database does not expose their identity or any details that can expose their personal identification. In addition, the user is informed on its privacy care with consent [35] and asked to approve in a contest his/her agreement for using the data for research purposes without misuse of the data similar to [35]. To maintain subject privacy, identifying features or details can be excluded. For instance, for video clips, only the skeletal features can be stored in the dataset. The user Consent is shown in Appendix.

F. COPYRIGHT AND LAW REGULATIONS

Before collecting the data from the SM we need to ensure its compatibility with law regulations and working according to the commercial rights and Intellectual Properties (IPs) of the SM provider. One key issue when collecting data for usage is to examine the SM term of conditions, and to ensure that the data is publicly available. Most SM enable free usage of the media, but some can restrict the usage for commercial usage. Aggregating with clinical database according to the SM usage rules [36]. For this we inform in the context the user of SMDC that the all process is under the SM conditions and the technology is aimed for research use and commercial use is limited

G. AGGREGATION WITH CLINICAL PRIORS AND DATABASES

The suggested SM database construction can be used for a first evaluation of research hypothesis in the absence of an available clinically verified database. This does not substitute the traditional buildup of a clinical dataset but can assist in the first verification stages of an algorithm or to validate hypothesis. With machine learning tools, the suggested SM dataset can be used for first training the model, show it consistency with clinical datasets. At a later stage when validated clinical dataset, or alternatively the labels are verified with medical experts, the ML can be fine-tuned. This enables enriching the data, while maintaining the restriction of the validated clinical dataset. When the database is clinically validated by correlating it to real clinical data, it can be used to enrich the clinical data and improve its generalization properties, since it is compromised from aggregation of the SM and the clinical insights. It can save computational resources, as fine tuning usually has lower computation requirements. In addition, it is expected to have a lower clinical dataset size.

III. CLINICAL DATABASE CONSTRUCTION EXAMPLE OF ADHD WITH A VIDEO DATASET

This new scheme for building databases was tested on ADHD neurological disorder where the data was videos. The database for ADHD, we used data extracted from YouTube videos to investigate ADHD vs. non-ADHD subjects according to their video tags. Using our scheme, we separated to demographic information of male vs. female, and used activity context of frontal while sitting. We validated the labels with an expert clinician for the hyperactivity part of ADHD.

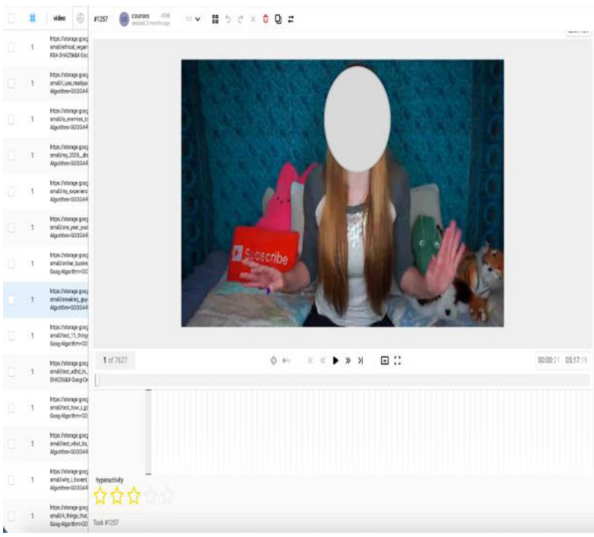

FIGURE 3. Clinical labeling gui for of YouTube clips.

A. REQUIRED DATABASE REQUESTS

In this study, we formed a dataset for ADHD from YouTube SM consisting of male and female subjects. Figure 3 shows the GUI (graphic user interface) for ADHD like user requires.

B. DATA EXTRACTION

In this study, a dataset of user generated content from YouTube was created to investigate attention deficit hyperactivity disorder (ADHD) and non-ADHD subjects. The videos were self-labeled, with individuals diagnosed or experienced with ADHD used as the true label for the ADHD group and videos without any ADHD-related content were used for the non-ADHD group. A total of 300 videos were collected in the dataset before filtering. The videos were scaled down to 30 fps (frames per second) and their resolution was changed to 720×1280 pixels for standardization.

C. DEMOGRAPHIC DATA RETRIEVAL

Demographic data was retrieved from the user database preferences. In our case study, the age groups were approximately between 20-40 years, and gender was male and female. Ethnicity was not included. Age and gender estimation can be retrieved by the labels attached to the multimedia, or by filtering the data using the preference using methods applied on the videos [37]. Visual examination can be used for verification. In our case study, we used visual examination for verification of the gender and age group.

D. LABELING

In this study, we used two methods for labeling the data for all clips. Both Self-Labeling and Clinical Expert Labeling were performed with a labeling application [26]. Additionally, the preference of gender was used as an additional label to compare the gender classification differences.

1) AUTOMATED LABELING

Our automatic labels were based on video clips self-labeling of subject's experiences with ADHD or their ADHD diagnosis. We believe that self-labeling is mostly of subjects that are clinically diagnosed with ADHD. Yet the continuous ADHD severity is believed to be correlated with the self-labeling under assumption that the subjects want to share with their circle of followers their true experience. Thus, self-labeling may reveal insights into the subjective experiences of individuals with ADHD, which could help to inform future research and treatment strategies. For the neuro-typical control group, of subjects not diagnosed with ADHD, we choose random videos under the limitation of the demographic constraints.

To validate the data labels, we examined manually to see that the videos were of real subjects and not of AI based bots. We further assume that the machine learning techniques we use that can cope with certain level of label noise [33]. Further techniques of comparing auto-label and cross validation with the data content are planned to be implemented in future.

2) CLINICAL EXPERT LABELING

To ensure the accuracy of our labels, we used a two-step process. First, we had an expert independently label the collected videos. To do so we used a labeling tool called "Label Studio" [26] to create an app that allows professionals to label the ADHD videos.

We focus mostly on aspects of hyperactivity, that have a clear motor projection that can be observed by the video recording, but less on the other non-motor aspects of the disease like attention that requires more interaction with other people and stimulations. Still, research works have shown that motor symptoms and attention are correlated, and most of the subjects who suffer from ADHD have both [28].

The clinical scoring application enable to rate each subject video clip on a scale of 1-5 on the scale of hyperactivity. The application was sent to a clinical expert to generate a labeled dataset. We then calculated inter-rater reliability scores to assess the consistency of the labeling. Figure 3 shows a labeling utility GUI example.

E. CONTEXT AWARE INFORMATION

To increase the prediction model performance, we tried to reduce the ambiguity of the subject activity to have similar action type. This can enable finding features that are significant to the action and enable to filter artifactitious labels. In this study, we chose to use without loss of generality, subjects within sitting pose and explore their upper body part. Consequently only videos featuring a single subject and containing a monologue or storytelling element were retained for analysis.

F. DATA VERIFICATION AND CLEANING

In the process of constructing a clinical database from SM, with a specific focus on video clips, the integration of video data introduces unique challenges in terms of data cleaning due to its multimedia nature. Video content often demands a more intricate level of processing compared to traditional clinical data due to its inherent complexity.

To ensure the quality and reliability of the dataset, the videos were cleaned and filtered based on various criteria, including gender and age of the subjects, presence of noise and banners, and editing style. Then we extracted only videos featuring the activity type of interest (upper part exposure with a monologue or storytelling element).

The cleaning has 3 stages: 1) remove heavily edited video segments; 2) size standardization; and 3) frame rate equalizer. For the segment removal, unlike traditional clinical data that exhibits typical consistency and continuity, video content frequently consists of edited segments or sub-clips grouped together to convey a specific message. Within our project, we systematically removed heavily edited sections from videos and excluded those that underwent extensive alterations. The data consisted after the verification and cleaning stage 40, and 38 females and males videos, respectively.

To cross validate the database quality, we employed outcomes from a study [38] and cross-referenced the extracted features to confirm that our collected dataset exhibited comparable feature distribution and discernible distinctions between subjects with ADHD and those without.

G. DATA PRE-PROCESSING

For the size standardization, the lengths of videos can display considerable variation, spanning from mere one-minute clips to extensive recordings lasting over an hour. Thus, ensuring a standardized data representation format becomes imperative for facilitating meaningful comparisons across the database. For frame rate equalization, the fluctuating frame rates present within video content can substantially influence the perception and analysis of the visual material. To address this, a critical concern is to establish consistency. Consequently, we implemented a frame rate adjustment algorithm that systematically resamples videos.

H. SUB-CLIP PARTITIONING

The videos can be divided into sub-clips to enhance machine learning diversity gained from different scenes. This empirical investigation facilitated the refinement of the data augmentation technique, resulting in an augmented dataset that better represented the underlying video content and enhanced the training process. Independent analysis of each sub-clip, and then integration of all the scenes. This requires optimizing the observation window duration to convey minimal time that requires to obtain sufficient data for independent diagnosis. Yet, the window size should not be too long, to lose the effect of diversity of the different time periods. The clips were chosen to have overlap to enrich the dataset and for consistency of the sub-clips content. By utilizing this approach, a greater number of instances were generated, leading to the creation of a more extensive and diverse dataset as shown in Fig 4.

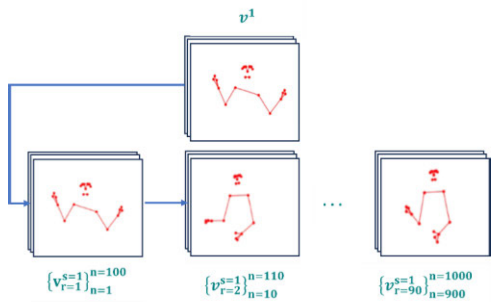

FIGURE 4. Sub-clip partitioning example of video $v_{\square}^{1}$ with 1000 frames that are split into 100 Frame Long sub-clips with 10 frames overlap.

Figure 5 shows the data partition to sub-clips. Let's denote the i'th subject video clip as $v_{\square}^{s}$, and the n'th frame, n = 1: N, as. To facilitate systematic analysis, the video was partitioned into sub-clips of fixed length, M, with an overlap of size K.

$$\left\{v_r^s\right\}_{r=1}^{r=(N-M)/K} \tag{1}$$

I. FEATURE EXTRACTION

In our study, we leveraged a comprehensive set of spatial and kinematic features extracted from individual sub-clips, following the methods outlined in references [17], and [39]. These features are derived from Mediapipe's 3D skeleton keypoints (landmarks) [40] extracted per frame. For every keypoints, we computed the distances, speeds, and accelerations of the keypoints between consecutive frames. Subsequently, we aggregate these features for the entire sub-clip using analytical techniques such as mean, median, standard deviation, and variance. To capture additional spatial information, we also calculate speed correlation, volume, and area for each joint throughout the entire sub-clip. This comprehensive approach to feature extraction enhances our ability to discern meaningful patterns and characteristics within the data, contributing to the robustness and discriminative power of our machine learning model.

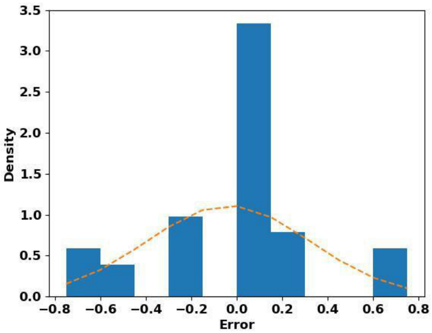

FIGURE 5. Database label vs expert rating.

J. ADHD RECOGNITION CLASSIFIER

The encouraging outcomes observed in our study provided the impetus for adopting a binary classification methodology to discern ADHD instances. We optimized the Naive Bayesian classifier [41], drawn to its simplicity and effectiveness in handling features with interdependencies. This classifier is based on Bayes' theorem and operates under the "naive" assumption that features are conditionally independent given the class label, making it well-suited for various machine learning applications. The utilization of the Naive Bayesian classifier facilitated not only the successful classification of ADHD cases but also laid the foundation for a robust benchmark in the realm of ADHD recognition. Its efficient handling of feature interdependencies, along with its ease of implementation, positions this classifier as a noteworthy choice for our classification task. These results not only contribute to the immediate goal of accurate ADHD recognition but also offer valuable insights for future research endeavors in the broader landscape of mental health classification using machine learning techniques.

IV. ADHD RECOGNITION RESULTS AND DISCUSSION

The results related to ADHD using the database. First, we show validity of the database compared to other research data and prior knowledge. Second, we validate our suggested labeling based on self-labeling with expert labeling, with our application platform. Then we show results of ADHD recognition using our database for both labels and show their compatibility. We discuss the differences in the labeling, and the data quality considerations.

A. TESTING PROCEDURE

We tested the data sets with leave-one out on the all-dataset size. During the testing phase, sub clips were extracted from previously unseen videos, and predictions were made for each sub clip independently. To achieve a more accurate classification for the entire video, an aggregation technique was employed. The predictions from the sub clips were aggregated using the majority of voting aggregation method to determine the final classification for the whole video.

B. DATABASE CLINICAL VERIFICATION

To validate the extracted database and to show its clinical feasibility, we tested the extracted data and the extracted labels separately. For the extracted data, we compared the data distribution and structure to the one from the ADHD database in [38]. For the labels' verification, we compared our self-tagged labels to medical expert (in the field of ADHD) scoring.

For the data clinical validation, we used as a reference the work in analyzed the movement of children sitting in a classroom skeletal information derived by Kinect (Microsoft Inc.) sensor. For this we used the kinematic features of the elbow, shoulder, and wrist of right and left body parts. We approximated the mean relative displacement of the 6 body parts over time with the mean velocity similar to [17].

To examine the consistency of the database we examine the mean velocity ratio in the observation window which is a measure of the subject activity profile. The mean velocity ratio between ADHD and non-ADHD is given by:

$$R_j = \frac{\bar{v}_j^{ADHD}}{\bar{v}_j^{nonADHD}}, \tag{2}$$

where $\bar{v}_j^{ADHD}$ is the j'th joint mean velocity of the ADHD, and non-ADHD subjects.

Table 1 shows the mean velocity ratio for 6 joints of ADHD vs control subjects as extracted from our database in compare to the one extracted in the work in [38] for ADHD vs non. It can be observed that for all joints ADHD kinematics as measured by mean velocity in observation window tend to be higher compared to the neurotypical group (non-ADHD), similar to the work in [38]. The mean difference between the groups is 22%, which is relatively small with t-test p_values of less than 0.001, which was lower than the reference work, where for the two wrists the data was less significant between the groups. The mean and standard deviation of the ratio between features comparing the correlation and significance of our features vs the other dataset resulted in similar results indicating the validity of our database.

TABLE 1. Mean velocity ratio of ADHD vs none of the database constructed from our technology vs the work in [30].

Feature	Our SMDC R_j	t-test p_value	R_j from [30]	t-test p_value
Left shoulder	30%	<0.001	20%	<0.001
Left wrist	4%	<0.001	32%	0.105
Left elbow	26%	<0.001	18%	<0.001
Right shoulder	20%	<0.001	38%	<0.001
Right wrist	31%	<0.001	9%	0.003
Right elbow	25%	<0.001	19%	<0.001

For the ADHD label we used the service of and expert from ADHD diagnostics institute (Kishurei-lemida Inc, Israel). The rater reviewed each clip, and rated from the video the hyperactivity level based on the subject activity profile and

DSM-5 definitions [42]. The medical expert gave each clip a score of hyperactivity between 1-5, where 1 is strong non-hyperactive, 2 is weak non- hyperactive, 3 is neutral or slight ADHD 4-is hyperactive, and 5 is strong hyperactive.

Figure 5 shows the distribution of medical expert diagnosis errors compared to the dataset labels showing a relatively Gaussian distribution, with mean error of -0.04 and standard deviation of 0.36. The correlation coefficient between the two labels was 0.44 (in range of -1 to 1). To validate the binary and the scale, we used scores 3-5 as ADHD, and 1-2 as non. The accuracy of our database label compared to the expert label was 0.69. The accuracy of nearly 0.7 is relatively high compared to the expert label that captured only hyperactivity while our labeling was based on self-labeled that captured different aspects of ADHD that included inactiveness. In addition, sometimes the subjects were medicated, and the expert label couldn't assessed correctly hyperactivity symptoms that are assumed to ease by the medication ("on" state). Thus, the self-label reference may be more accurate. In future the database can include information about the different symptoms of ADHD, and each can be evaluated separately, and information about the medication dose and frequency.

C. FEATURES REPRESENTATION AND IMPORTANCE

The features extracted from the model represent the subject's movement and are aimed to capture fine motor control and attention-related behaviors. The features are calculated based on extracted skeleton joints for each frame from the upper body. Since ADHD is often associated with impulsivity and difficulties in maintaining attention, capturing hand and head movements could provide insights into these aspects [30]. The features are kinematics features from the upper body parts from our upper body dataset. The features include the following features motor clusters: kinematic features of speed, acceleration between the joints in consecutive frames; Statistical features of mean, median, standard deviation, and Pearson Correlation of joints with other joints; and the 3D volume and area of each joint using the convex hull method. The total number of features resulted in 598 features. In our feature evaluation, we employed the SHAP (SHapley Additive exPlanations) [43] method for feature selection, SHAP calculates the influence of each feature on the prediction relative to all other features. To explore the model, we can explore the features, since the features extraction, which demonstrate the explainability of our method for clinical use.

The suggested methodology can also derive natural biomarkers to distinguish between ADHD and neurotypical (non-ADHD) subjects and provide a breakdown of model performance by different demographic groups like age, gender, and ethnicity to highlight any potential disparities. To demonstrate this, without loss of generality, we explore the gender effect on the prediction model.

This allows us to capture the unique patterns and characteristics of ADHD symptoms within each gender. The five most significant features for female subjects were the upper limbs volume, fingers movement volume, and eye volume, which represents increase movement of the limbs, hands and head for females that were tagged with ADHD. Male subjects features were mouth and eye distance, speed and acceleration which represents increased head movement for males tagged with ADHD. For all, the p-value [44] between the two genders was lower than 1e-5.

We observe contrasting key features between genders; while females exhibit a varied array including head, fingers, and upper body limb movements, males predominantly show significant head movement, suggesting distinct manifestations of ADHD across genders. Our findings for increased volume of arms and hand movement (in 3D coordinates) as hyperactivity biomarker was also supported with research related to ADHD and hyperactivity [45], [46], [47].

Figure 6.a and 6.c shows the t-SNE (t-Distributed Stochastic Neighbor Embedding) features representation [48] for the ADHD vs none utilizing all 598 features (6.a female, 6.c male).

In Figure 6.b and 6.d, shows the t-SNE representation with only the ten most significant features (6.b female, 6.d male). The decision boundary was derived by a Gaussian Naive Bayes model. From the representation we can see that the ADHD and non-ADHD (control) are separable into clusters, even with only ten motor features. These features can be candidate to be ADHD biomarkers in clinical future research with further clinical verification.

D. ADHD RECOGNITION ACCURACY DIFFERENCES BETWEEN GENDERS

The model was trained with the model labels, which are based on the video clips self-labeling. This methodology was designed to capture the intricate and subjective characteristics of ADHD, in particular to the observable hyperactivity. To evaluate the model accuracy, we compare it separately to the model labels and to the medical expert labels for both genders.

Figure 7 shows the ROC for male, female results. The medical expert achieved a 0.78 accuracy, 0.77 F1 score and area under the curve (A UC) of 0.77 on the female dataset and, 0.85 accuracy, 0.86 F1 score and area under the curve (AUC) if 0.85 on the male dataset. Our model achieved a 0.83 accuracy 0.83 F1 score and area under the curve (AUC) if 0.82 on the female dataset and a 0.81 accuracy 0.81 F1-score and area under the curve (AUC) if 0.91 on the male dataset. Thus, the ROC curves illustrate the discriminative performance of the model across various thresholds for both model labels (self-labeling) and medical expert labels in the male and female datasets. Table 2 summarizes the model evaluation for the two genders with classification accuracy, sensitivity, and specificity. The model demonstrates commendable accuracy, with self-labeling achieving an overall accuracy of 0.859 for both genders. Notably, the self-labeling ROC curve for males exhibits a particularly high area under

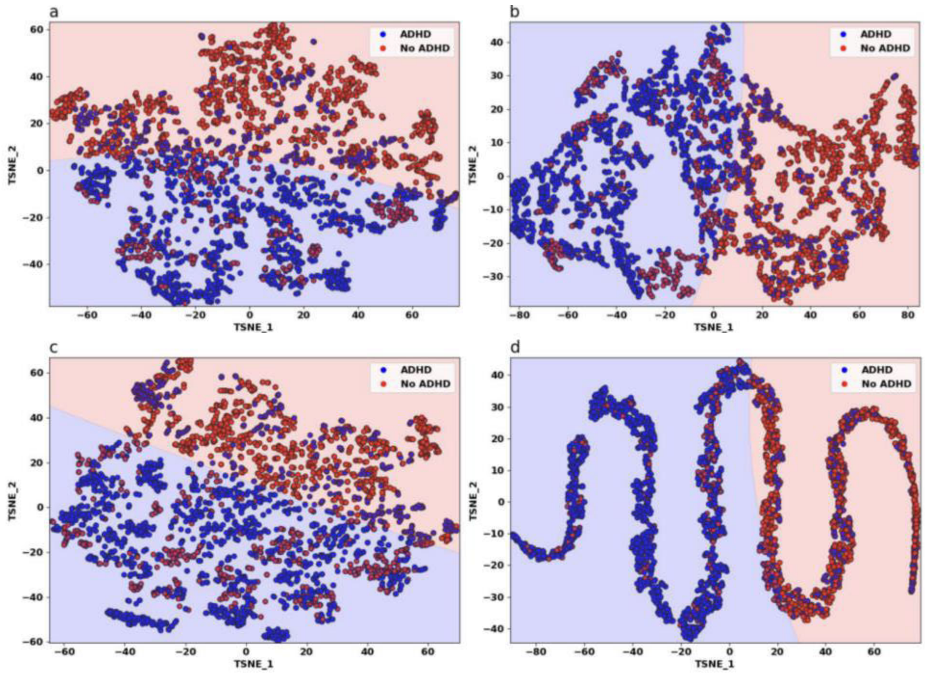

FIGURE 6. Figure 6.a, And 6.b Describe The2-D t-SNE representation of ADHD vs. none (neurospecific control) with using all the features, and the 10 most Significant features for female subjects and Figs. 6.b And 6.d for male subjects.

TABLE 2. Model evaluation.

Model	Accuracy	F1	Sensitivity	Specificity
Female				
Suggested Model	0.83	0.83	0.77	0.88
Medical Expert	0.78	0.77	0.88	0.66
Male				
Suggested Model	0.81	0.81	1.0	0.66
Medical Expert	0.88	0.86	0.71	1.0

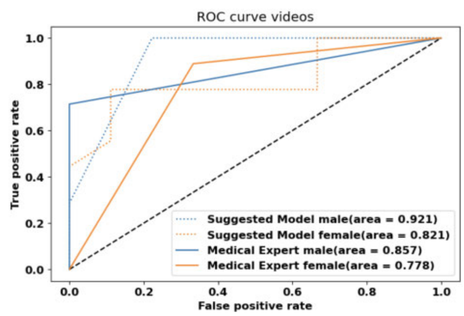

FIGURE 7. Male, female, and male & female ROC curve in reference to the model labels, based on the clips self-labeling, and the independent medical expert labels.

the curve (AUC) of 0.921, indicating strong discriminatory power. For females, the self-labeling AUC is 0.821, reinforcing the model's robustness. The medical expert labels present

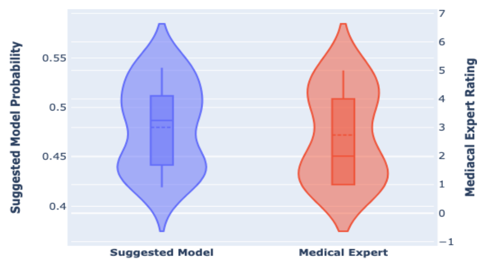

FIGURE 8. Model prediction distribution vs expert labels scoring.

lower overall accuracy (0.82), with ROC curves for males and females yielding AUCs of 0.57 and 0.778, respectively.To further validate the model outcomes, we compare our total model's prediction distribution with the medical expert's predictions. Figure 8 shows both distributions. We can observe similar distribution of our model and expert scores. The model has mean estimation of 0.47 (from 0 to 1), while the medical expert has slightly higher mean estimation of 2.7 (scale of 1-5), which shows low bias of the medical rater towards hyperactivity compared to the model score. This can be explained by the more observable hyperactivity ADHD's sub-score to the observer compared to the more internal intension sub-score that is evidence in the model labels, which are based on the subject's self-report.

V. CONCLUSION AND FUTURE WORK

In this work, we map the challenges in building a SM (social media) based database and define mechanisms that

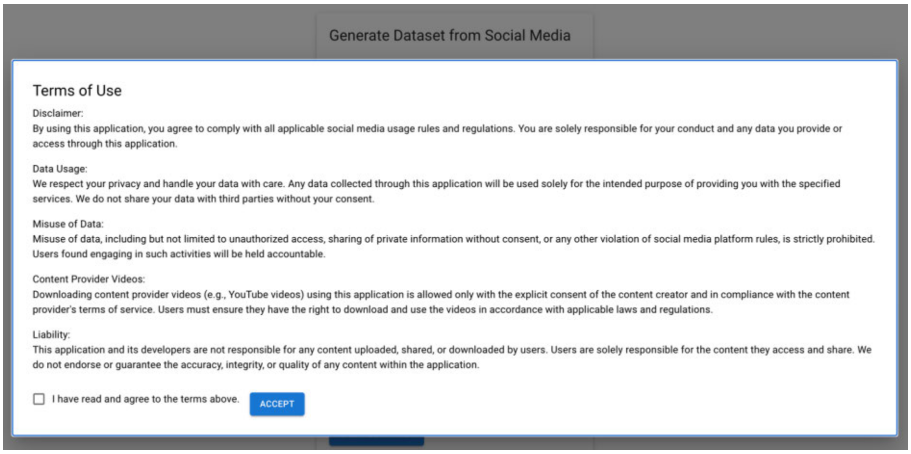

FIGURE 9. User consent from the application.

can potentially enable researchers to build such a database. To demonstrate the process and prove feasibility of technology we decided to focus in this study on the field of neurological diseases and disorders and behavioral databases. For this pilot study we built a software utility named SMDC (social medica database constructor). We then demonstrate this in a case study of ADHD subjects and construct a database, utilizing desired demographic information as defined by the database requirements. The video clips can be from any publicly available multimedia resources. The labeling was based on harvesting from the video clip tagging, which can be seen as a self-report mechanism. To verify the labeling, we validated the data labeling with independent scoring by a medical expert in the field of ADHD and showed high correlation of over 70% between the scores. We further validated the constructed data features by comparing to clinically validated features and show high consistency for all six of the found mental ADHD discriminative features, with p-value lower than 0.001. We then showed that with a naïve-Bayes classifier using this database we can achieve over 80% accuracy in ADHD recognition.

The results of this work can open the window to construct useful clinically validated databases from social network multimedia information. Since it might not be possible to obtain full accuracy with such an automated process, we emphasize that the goal of this work is not to fully replace clinical datasets and controlled environment testing, but rather to assist, in the following tasks: 1) better design of clinical experiment design specification like demographic information or desired data sample size; 2) quick tool to verify real-life biomarkers that are not restricted to controlled settings and reflect wide population in their home environment settings and by this to reduce medical expert subjective biases; 3) save medical expert time and reduce training of large deep-learning models, by using clinical data for fine tuning only. By properly using the dataset from the suggested technology, the total results should be more accurate than only limited size clinical data.

This study, due to its use of a single subject speaking to the camera, is limited to activity-motor related symptoms related to hyperactivity. Still, since in ADHD there is high correlation between the hyperactivity and the attention deficit symptoms, we can assume the work is valuable for total ADHD recognition. In future, more complex videos that measure interaction between subjects and their response to different stimulations, can directly assess the additional attention biomarkers. Furthermore, here we explore briefly the gender difference with different biomarkers for each gender, but a full investigation of gender and other demographic groups is planned to be further investigated in follow-up research. The limitations of using social media data, and variability in data quality should also be investigated in future research with massive data.

The relatively straightforward process of collecting additional videos, coupled with the identified research directions, presents exciting opportunities for future investigations. Another future research direction is to validate the SMDC with other medical conditions, and media types. Future work entails the incorporation of tabular data and the assimilation of diverse modalities such as audio and text and enriching the clinical validation of the dataset. Additionally, there is a scope to include information on drug usage, dosage, and frequency, providing a more comprehensive perspective.

APPENDIX

See Figure 9.

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REFERENCES

[1] A. Barbu, D. Mayo, J. Alverio, W. Luo, C. Wang, D. Gutfreund, J. Tenenbaum, and B. Katz, "ObjectNet: A large-scale bias-controlled dataset for pushing the limits of object recognition models," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 32, 2019, pp. 1–11.

[2] C. Ricós, V. Alvarez, F. Cava, J. V. García-Lario, A. Hernández, C. V. Jiménez, J. Minchinela, C. Perich, and M. Simón, ''Current databases on biological variation: Pros, cons and progress,'' *Scandin. J. Clin. Lab. Invest.*, vol. 59, no. 7, pp. 491–500, Jan. 1999.

[3] R. J. Chen, J. J. Wang, D. F. K. Williamson, T. Y. Chen, J. Lipkova, M. Y. Lu, S. Sahai, and F. Mahmood, ''Algorithmic fairness in artificial intelligence for medicine and healthcare,'' *Nature Biomed. Eng.*, vol. 7, no. 6, pp. 719–742, Jun. 2023.

[4] J. Moore, Y. Celik, S. Stuart, P. Mcmeekin, R. Walker, V. Hetherington, and A. Godfrey, ''Using video technology and AI within Parkinson's disease free-living fall risk assessment,'' *Sensors*, vol. 24, no. 15, p. 4914, Jul. 2024.

[5] Ž. Tamulis, M. Vasiljevas, R. Damaševičius, R. Maskeliunas, and S. Misra, ''Affective computing for ehealth using low-cost remote Internet of Things-based emg platform,'' in *Intelligent Internet of Things for Healthcare and Industry*. Cham, Switzerland: Springer, 2022, pp. 67–81.

[6] P. Gundecha and H. Liu, ''Mining social media: A brief introduction,'' *New Directions Inform., Optim., Logistics, Prod.*, pp. 1–17, Sep. 2012. [Online]. Available: https://pubsonline.informs.org/doi/10.1287/educ.1120.0105

[7] A. Abbas, M. Ali, M. U. S. Khan, and S. U. Khan, ''Personalized healthcare cloud services for disease risk assessment and wellness management using social media,'' *Pervas. Mobile Comput.*, vol. 28, pp. 81–99, Jun. 2016.

[8] C. Khorakhun and S. N. Bhatti, ''Remote health monitoring using online social media systems,'' in *Proc. 6th Joint IFIP Wireless Mobile Netw. Conf. (WMNC)*, Apr. 2013, pp. 1–8. Accessed: Sep. 24, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6548953/?casa_token=t8dwwSBEr1oAAAAA:Y-8Ya-eHvw0h_kGCWwswmaXOdeYcXecXkcWg1FUffl1_hBIG8eiCKrdakydF5tqVeYspspKQy4I

[9] F. Stasolla, V. Perilli, and R. Damiani, ''Self monitoring to promote on-task behavior by two high functioning boys with autism spectrum disorders and symptoms of ADHD,'' *Res. Autism Spectr. Disorders*, vol. 8, no. 5, pp. 472–479, May 2014.

[10] D. Daley and J. Birchwood, ''ADHD and academic performance: Why does ADHD impact on academic performance and what can be done to support ADHD children in the classroom?'' *Child, Care, Health Develop.*, vol. 36, no. 4, pp. 455–464, Jul. 2010.

[11] A. S. Bell, ''A critical review of ADHD diagnostic criteria: What to address in the DSM-V,'' *J. Attention Disorders*, vol. 15, no. 1, pp. 3–10, Jan. 2011.

[12] Subcommittee on Attention-Deficit/Hyperactivity Disorder, Steering Committee on Quality Improvement and Management, ''ADHD: Clinical practice guideline for the diagnosis, evaluation, and treatment of attention-deficit/hyperactivity disorder in children and adolescents,'' *Pediatrics*, vol. 128, no. 5, pp. 1007–1022, 2011.

[13] S. Jaiswal, M. F. Valstar, A. Gillott, and D. Daley, ''Automatic detection of ADHD and ASD from expressive behaviour in RGBD data,'' in *Proc. 12th IEEE Int. Conf. Autom. Face Gesture Recognit. (FG)*, May 2017, pp. 762–769.

[14] M. Leo, G. M. Bernava, P. Carcagnì, and C. Distante, ''Video-based automatic baby motion analysis for early neurological disorder diagnosis: State of the art and future directions,'' *Sensors*, vol. 22, no. 3, p. 866, Jan. 2022.

[15] G. Blumrosen, M. Uziel, B. Rubinsky, and D. Porrat, ''Noncontact tremor characterization using low-power wideband radar technology,'' *IEEE Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 674–686, Mar. 2012, doi: 10.1109/TBME.2011.2177977.

[16] G. Blumrosen, B. Fishman, and Y. Yovel, ''Noncontact wideband sonar for human activity detection and classification,'' *IEEE Sensors J.*, vol. 14, no. 11, pp. 4043–4054, Nov. 2014, doi: 10.1109/JSEN.2014.2328340.

[17] G. Blumrosen, Y. Miron, N. Intrator, and M. Plotnik, ''A real-time Kinect signature-based patient home monitoring system,'' *Sensors*, vol. 16, no. 11, p. 1965, Nov. 2016, doi: 10.3390/s16111965.

[18] R. Gao, K. Deng, and M. Xie, ''Deep learning-assisted ADHD diagnosis,'' in *Proc. 3rd Int. Symp. Artif. Intell. Med. Sci.*, vol. 18, Oct. 2022, pp. 142–147.

[19] L. He, F. He, Y. Li, X. Xiong, and J. Zhang, ''A robust movement quantification algorithm of hyperactivity detection for ADHD children based on 3D depth images,'' *IEEE Trans. Image Process.*, vol. 31, pp. 5025–5037, 2022.

[20] C.-S. Ouyang, Y.-H. Chiu, C.-T. Chiang, R.-C. Wu, Y.-T. Lin, R.-C. Yang, and L.-C. Lin, ''Evaluating therapeutic effects of ADHD medication objectively by movement quantification with a video-based skeleton analysis,'' *Int. J. Environ. Res. Public Health*, vol. 18, no. 17, p. 9363, Sep. 2021.

[21] K. Pelc, C. Kornreich, M.-L. Foisy, and B. Dan, ''Recognition of emotional facial expressions in attention-deficit hyperactivity disorder,'' *Pediatric Neurol.*, vol. 35, no. 2, pp. 93–97, Aug. 2006.

[22] L. M. Connelly, ''Demographic data in research studies,'' *Medsurg Nursing*, vol. 22, no. 4, pp. 269–271, 2013.

[23] G. Batra, S. Aktaa, L. Wallentin, A. P. Maggioni, C. Wilkinson, B. Casadei, and C. P. Gale, ''Methodology for the development of international clinical data standards for common cardiovascular conditions: European unified registries for heart care evaluation and randomised trials (EuroHeart),'' *Eur. Heart J.-Quality Care Clin. Outcomes*, vol. 9, no. 2, pp. 161–168, Feb. 2023.

[24] R. Doshi, K. K. Hiran, M. Gök, E.-S. M. El-kenawy, A. Badr, and M. Abotaleb, ''Artificial intelligence's significance in diseases with malignant tumours,'' *Mesopotamian J. Artif. Intell. Healthcare*, vol. 2023, pp. 35–39, Jul. 2023.

[25] M. M. Eid, W. Yundong, G. Benneh Mensah, and P. Pudasaini, ''Treating psychological depression utilising artificial intelligence: AI for precision medicine- focus on procedures,'' *Mesopotamian J. Artif. Intell. Healthcare*, vol. 2023, pp. 76–81, Dec. 2023.

[26] *Open Source Data Labeling*. Accessed: Aug. 29, 2023. [Online]. Available: https://labelstud.io/

[27] X. Liu, S. C. Rivera, D. Moher, M. J. Calvert, and A. K. Denniston, ''Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: The CONSORT-AI extension,'' *Lancet Digit. Health*, vol. 2, no. 10, pp. e537–e548, 2020.

[28] E. Seesjärvi, J. Puhakka, E. T. Aronen, J. Lipsanen, M. Mannerkoski, A. Hering, S. Zuber, M. Kliegel, M. Laine, and J. Salmi, ''Quantifying ADHD symptoms in open-ended everyday life contexts with a new virtual reality task,'' *J. Attention Disorders*, vol. 26, no. 11, pp. 1394–1411, Sep. 2022.

[29] W. Fan, F. Geerts, and X. Jia. (2007). *Improving Data Quality: Consistency and Accuracy*. ACM. Accessed: Sep. 17, 2024. [Online]. Available: https://documentserver.uhasselt.be/handle/1942/7912

[30] M. Wan, T. Safavi, S. K. Jauhar, Y. Kim, S. Counts, J. Neville, S. Suri, C. Shah, R. W. White, L. Yang, R. Andersen, G. Buscher, D. Joshi, and N. Rangan, ''TnT-LLM: Text mining at scale with large language models,'' in *Proc. 30th ACM SIGKDD Conf. Knowl. Discovery Data Mining*, vol. 7. Barcelona, Spain: ACM, Aug. 2024, pp. 5836–5847, doi: 10.1145/3637528.3671647.

[31] E. Tasci, Y. Zhuge, K. Camphausen, and A. V. Krauze, ''Bias and class imbalance in oncologic data—Towards inclusive and transferrable AI in large scale oncology data sets,'' *Cancers*, vol. 14, no. 12, p. 2897, Jun. 2022.

[32] P. Chen, G. Chen, J. Ye, and P.-A. Heng, ''Noise against noise: Stochastic label noise helps combat inherent label noise,'' in *Proc. Int. Conf. Learn. Represent.*, 2021, pp. 1–20. Accessed: Sep. 15, 2024. [Online]. Available: https://openreview.net/forum?id=80FMcTSZ6J0

[33] A. Ghosh, H. Kumar, and P. S. Sastry, ''Robust loss functions under label noise for deep neural networks,'' in *Proc. AAAI Conf. Artif. Intell.*, 2017, pp. 1–7. Accessed: Sep. 15, 2024. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/10894

[34] M. Marsch, J. Grossklags, and S. Patil, ''Won't you think of others: Interdependent privacy in smartphone app permissions,'' *Proc. ACM Hum.-Comput. Interact.*, vol. 5, no. CSCW2, pp. 1–35, Oct. 2021.

[35] S. J. De and A. Imine, ''On consent in online social networks: Privacy impacts and research directions (short paper),'' in *Proc. 13th Int. Conf. Risks Secur. Internet Syst. (CRiSIS)*, in Lecture Notes in Computer Science. Cham, Switzerland: Springer, 2019, pp. 128–135, doi: 10.1007/978-3-030-12143-3_11.

[36] P. G. Lange, ''Publicly private and privately public: Social networking on YouTube,'' *J. Comput.-Mediated Commun.*, vol. 13, no. 1, pp. 361–380, Oct. 2007.

[37] A. S. Kharchevnikova and A. V. Savchenko, ''Neural networks in video-based age and gender recognition on mobile platforms,'' *Opt. Memory Neural Netw.*, vol. 27, no. 4, pp. 246–259, Oct. 2018.

[38] M. Sempere-Tortosa, F. Fernández-Carrasco, F. Mora-Lizán, and C. Rizo-Maestre, ''Objective analysis of movement in subjects with ADHD. Multidisciplinary control tool for students in the classroom,'' *Int. J. Environ. Res. Public Health*, vol. 17, no. 15, p. 5620, Aug. 2020, doi: 10.3390/ijerph17155620.

[39] J.-W. Kim, J.-Y. Choi, E.-J. Ha, and J.-H. Choi, ''Human pose estimation using MediaPipe pose and optimization method based on a humanoid model,'' *Appl. Sci.*, vol. 13, no. 4, p. 2700, Feb. 2023.

[40] V. Bazarevsky, I. Grishchenko, K. Raveendran, T. Zhu, F. Zhang, and M. Grundmann, ''BlazePose: On-device real-time body pose tracking,'' 2020, *arXiv:2006.10204*.
[41] *Rish—An Empirical Study of the Naive Bayes Classifier.pdf*. Accessed: Jan. 19, 2024. [Online]. Available: https://sites.cc.gatech.edu/home/isbell/classes/reading/papers/Rish.pdf
[42] *DSM-5 Symptoms and Diagnosis of ADHD*. Accessed: Jul. 24, 2024. [Online]. Available: https://www.cdc.gov/ncbddd/adhd/diagnosis.html
[43] S. M. Lundberg and S.-I. Lee, ''A unified approach to interpreting model predictions,'' in *Proc. Adv. Neural Inf. Process. Syst.* Glasgow, U.K.: Curran Associates, 2017, pp. 1–10. Accessed: Feb. 17, 2024. [Online]. Available: https://papers.nips.cc/paper_files/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf
[44] J. C. De Winter, ''Using the student's t-test with extremely small sample sizes,'' *Practical Assessment, Res., Eval.*, vol. 18, no. 1, p. 10, 2019.
[45] T. A. Blondis, ''Motor disorders and attention-deficit/hyperactivity disorder,'' *Pediatric Clinics North Amer.*, vol. 46, no. 5, pp. 899–913, 1999.
[46] M. H. Teicher, Y. Ito, C. A. Glod, and N. I. Barber, ''Objective measurement of hyperactivity and attentional problems in ADHD,'' *J. Amer. Acad. Child Adolescent Psychiatry*, vol. 35, no. 3, pp. 334–342, Mar. 1996.
[47] E. M. Mahone, D. Bridges, C. Prahme, and H. S. Singer, ''Repetitive arm and hand movements (complex motor stereotypies) in children,'' *J. Pediatrics*, vol. 145, no. 3, pp. 391–395, Sep. 2004.
[48] L. Van der Maaten and G. Hinton, ''Visualizing data using t-SNE,'' *J. Mach. Learn. Res.*, vol. 9, no. 11, pp. 1–27, 2008. Accessed: Jan. 17, 2024. [Online]. Available: https://www.jmlr.org/papers/volume9/vandermaaten08a/vandermaaten08a.pdf?fbcl

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