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Spatial Blockchain-Based Secure Mass Screening Framework for Children With Dyslexia

MD. ABDUR RAHMAN[1], ELHAM HASSANAIN[1], MD. MAMUNUR RASHID[2], STUART J. BARNES[2], AND M. SHAMIM HOSSAIN[3,4], (Senior Member, IEEE)

[1]Department of Forensic Computing and Cyber Security, Faculty Computing and Cyber Sciences, University of Prince Mugrin, Madinah 41499, Saudi Arabia
[2]Consumer and Organizational Digital Analytics Research Centre, King's Business School, King's College London, London WC2B 4BG, U.K.
[3]Research Chair of Pervasive and Mobile Computing, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia
[4]Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

Corresponding author: M. Shamim Hossain (mshossain@ksu.edu.sa)

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ABSTRACT In this paper, we present a novel method, process, and system for calculating dyslexic symptoms, generating metric data for an individual user, community, or group in general. We present a mobile multimedia Internet of Things (IoT)-based environment that can capture multimodal smartphone or tab-based user interaction data during dyslexia testing and share it via a mobile edge network, which employs auto-grading algorithms to find dyslexia symptoms. In addition to algorithm-based auto-grading, the captured mobile multimedia payload is stored in a decentralized repository that can be shared with a medical practitioner for replay and further manual analysis purposes. Since the framework is language-independent and based on Blockchain and a decentralized big data repository, dyslexic patterns and a massive amount of captured multimedia IoT test data can be shared for further clinical research, statistical analysis, and quality assurance. Notwithstanding, our proposed Blockchain and off-chain-based decentralized and secure dyslexia data storage, management, and sharing framework will allow security, anonymity, and multimodal visualization of the captured test data for mobile users. This paper presents the detailed design, implementation, and test results, which demonstrate the strong potential for wider adoption of the dyslexia mobile health management globally.

INDEX TERMS Blockchain, dyslexia, auto-grading, mass screening, mobile multimedia health.

I. INTRODUCTION

Dyslexia is a cognitive disability impeding individuals in the ordinary process of reading, drawing, and writing [1]. Dyslexic children often demonstrate high intelligence, but the learning disability poses a particular challenge to typical modes of learning in schools [2]. Thus, early identification of the affliction is paramount in ensuring that appropriate assistance is provided by parents and schools [3]. Previous research has proposed various tests for identifying dyslexia in school children aged under 11 years [4]–[12], but the methods typically cannot be scaled up easily to a national level or tend to focus on one test modality. Various technological advancements such as IoT [13], tablet computers and mobile devices for health applications, widespread broadband Internet (including rural areas), mobile edge computing (MEC), smart health and big data analytics [14], [42], have provided significant new opportunities for finding symptoms of dyslexia. This study provides a framework for testing dyslexia symptoms using various modules via mobile cloud devices [43], IoT [44], and multimedia [45]. The mobile or tab-based test provides a low-cost method for widespread testing of dyslexia in schools, whereby results can be further interpreted by professional dyslexia therapists, all being mobile.

Dyslexia detection is a challenging prospect at the age of 4 or 5 when a child starts going to school. Since these gifted children have difficulty in reading [2], writing [9], and drawing [15], they fail to properly follow class lectures, prepare homework and perform in exams [16]. Hence, dyslexic children begin to become isolated from other children, attain poor grades, and may even forego future studies and associated professional careers [8], [9], and [17]–[21]. However, if symptoms are detected at an early stage, they can be addressed through assistive technologies and children can take part in regular schools [22]–[26]. Although some single modality tests for screening dyslexia are available [12], [18], and [27]–[33], they are limited in their ability to be scaled-up to a massive level. Thus, our proposed framework seeks to provide screening tests that can potentially be used globally, based on MEC, cloud computing, and independence from languages. More specifically, the present manuscript describes a more effective method and system for obtaining IoT data regarding a user's dyslexic activity and interactions. It provides a novel method and system for processing such data using system templates at the MEC layer to generate timely, accurate, relevant and actionable analytic metrics that participants, doctors and policy-makers can use to guide them towards better treatments and outcomes.

Due to recent advancements, more and more mobile or tab-based IoT devices are becoming connected with greater processing capability, which can support dyslexia testing and the screening process ubiquitously. For example, recent face, pupil, hand gesture, and voice recognition IoT devices can process data locally and upload the diagnosis data to the nearby MEC node [34]. MEC shows the potential to address the availability and improved connectivity, resilience, scalability, low latency, and real-time delivery of massive amounts of data, which the traditional cloud-only solution fails to guarantee [35]. The introduction of an MEC layer at the vicinity of the IoT sensors or users would allow mobility of users, ubiquitous mobile device-based access, saving bandwidth and processing resources, and incorporate security solutions before the processed data is sent to the cloud [36]. However, due to the stringent privacy, security and anonymity requirements of dyslexic patients' data, MEC requires the leveraging of technologies such as Tor and Blockchain [37]. These disruptive technologies together with MEC can allow anonymous and secure sharing of multimedia data [46] with any intended mobile stakeholder without the need for any central authority. A school, a patient or any IoT device can carry out any test activity or share test results or perform financial or payment transactions without the need for an intermediary, overcoming city or country-specific data format exchange complications. The chain of blocks containing the timestamped history of spatio-temporal activities and transactions related to the results of a particular dyslexia test or a user's test history containing spatio-temporal multimedia big data can be linked by cryptographic hashes within the Blockchain [38].

Among the security features of Blockchain are a fully decentralized peer-to-peer redundancy solution, providing a secure identity for each stakeholder, and support of smart contracts, which can be activated on spatio-temporal logic [39]. This has the potential to maintain the secrecy of dyslexic patients' data through the secure wallet and strong encryption, guaranteeing the service level agreement through transparency of the historical blocks at a low cost. The raw IoT data and the multimedia payload emanating from different smartphone and tab-based applications can thus be anonymized and at the same time be added to the Blockchain at the MEC node before it can be sent to the cloud. Once a dyslexic child's data is added to the Blockchain, the child can perform any number of on demand tests, visit different doctors and schools, in different spatial locations such as at home, in a therapy center, and medical institutions, giving dyslexia data mobile and ubiquitous access to the stakeholders [40]. Hence, together with Blockchain-based security, each dyslexic subject takes control of his or her data in mobile health scenarios.

In our proposed mobile health application scenario, the live eye, hand, and stylus movement during the test is securely captured from the smartphone or tab as a video, interweaved with the audio and spatio-temporal gaze focus. After the test finishes, the test module consisting of user drawings, the user-typed characters, and user interaction with the screen is saved as video and sent to the nearby MEC node. The MEC node employs auto-grading algorithms to find dyslexic patterns by analyzing multimedia IoT data, saving the final result in Blockchain and off-chain [41]. In this paper, we present the following novel contributions:

- An electronic dyslexia-screening tool in Arabic and English that can be adapted for any language.
- The ability to mass screen students and concurrently collect test results in a big data repository in a 20-minute period for the first time. The test incorporates four different modalities: a reading test, a writing test, a clock-drawing test, and a cognitive test through drawing family members, all with the eye-tracking modality augmented on top of these tests. The framework incorporates eye tracking and audio capture during the reading screening test. Since the final results are stored in Blockchain, the data remains secure and shareable with any number of stakeholders.
- A dyslexia indicative tool electronically instituted and auto graded, based on MEC and big data server-side analytics.
- The tool can be used for ages 8 and above, and is the only one of its kind available in the Arabic language.
- The system incorporates cognitive ability testing.
- The test modules are incremental in complexity, context-aware content and time duration, and cognitive challenges, depending on whether the subject is attending preschool, junior school, high school, college or university. The licenses can be distributed per student for in-home usage, or a volume license provided for a school, a district or even a whole ministry of education.
- The writing test is recorded as a video interaction session, which can be replayed at any time in the future, at any location, to retrace the writing technique specific for dyslexic patients.
- An auto grading ability is added to detect sloppiness, letter reversal, missed spellings and omitted words during a writing test.
- Electronic auto grading and video recording of the clock-drawing test gives a medical analyst the complete semantic experience of finding dyslexic patterns. The auto-grading algorithm can detect missing minute or hour hands, missing numbers, the order of hours, the location of hours, or dislocated or wrongly placed minute or hour hands.

- Results from auto-grading raise flags in each test module for each student so that the analyst can easily focus greater attention on those requiring confirmation of dyslexic patterns.
- Graphical representation of the overall score of all the modules allows the analyst to visualize and provide feedback on each of the test modules.
- A multimedia-based (text, audio, video and eye-tracking data) tablet and smartphone environment and big data-based server-side analytics, which can support millions of simultaneous screenings around the globe.
- Test modules are based on tablet PC, smartphone, IoT devices, and analyst screening, and registration modules are based on web services, so that the complete process is scalable.
- The available interaction patterns in the form of multimedia can be used by the specialized doctor for one-to-one further diagnosis, without any border.

The rest of the paper is organized in the following way. Section II shows the detailed system design, followed by implementation details in Section III and the test results in Section IV. Finally, we provide our conclusions in Section V.

II. SYSTEM DESIGN

Figure 1 illustrates the use case diagram of the overall system. The registration process for the student is illustrated, where the test administrator registers the school and students. The student takes the test from the tablet, within the proximity of the IoT devices, which are set up by the administrator. The client component in the tablet transfers the results and data to backend intelligence over MEC/cloud/Internet. The data analysis in the backend intelligence conducts analyses using auto-grading services. The final review is done through experts such as doctors and analyzers. The final reports are sent to policy handlers and stakeholders. From the individual's perspective, the dyslexia test is taken online in class. The subject can take a test using a smartphone, laptop, desktop, tablet or any other electronic, physical or mechanical means. The multimedia data is stored in the electronic device before being uploaded to the backend server through the network. The backend intelligence uses the big data analytics engine in the server/decentralized repository to store and process the data. The data is viewed by an expert using the expert client. The expert reviews auto-grading and multimedia before updating the results for view over the network. The results are available electronically but could be viewed via physical (e.g. paper) or other (e.g. audio) mediums, or the results made available to a group.

Figure 1 illustrates the use case for an intelligent performance analysis solution (PAS). The PAS system front end has interfaces for individuals, groups, companies and industry. Users' devices access the front end over the network to provide and receive feedback. The PAS module resides in the MEC or cloud connected to the Blockchain or decentralized repository, as a knowledge base. PAS provides services to external customers who require targeted assistance on analytics, in which case they interface with the intelligent backend system.

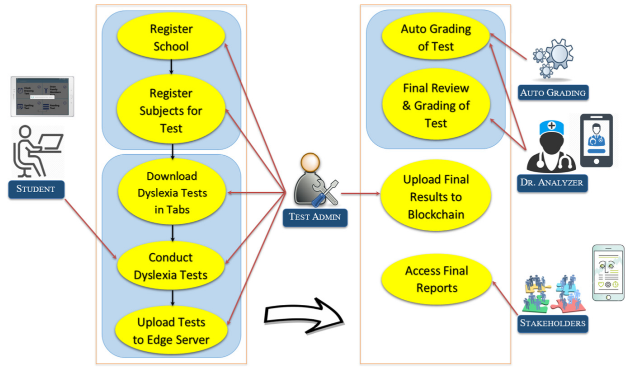

FIGURE 1. High level system use case diagram.

Figure 1 illustrates the use cases of the system at a high level. A first step is for a school to obtain licenses from the secure server and install the software onto a commensurate number of tablet PCs. Tests are then conducted and when completed, multimedia files with the results of the four test modules are uploaded to the big data server. The server processes individual multimedia files, which along with auto-grading results then become available to dyslexia experts to examine and approve. Auto-grading uses leading edge image processing and gaze-tracking algorithms, aiding the medical analyst in filtering and flagging dyslexia symptoms in test modules. Overall results become available to the relevant stakeholders, through a Blockchain-based secure DApps.

Figure 2 is a block diagram illustrating the different modules within a screening application where the user input is taken. The modules in Figure 2 have interfaces to the users, and one-to-one connectivity to the backend intelligence. The modules in the backend intelligence that provide active support and computation work based on stimuli from the blocks in Figure 2. For example, the user interface for the input module receives user input and relays it to the back-end intelligence user interface. Similarly, the classification module interfaces with the back-end classification module.

Various modules of the software resident in the computing device used by the test subject are illustrated in Figure 2. The Input Module may receive inputs from other systems within or external to the application, and from users and experts such as doctors. The Classification Module may contain system templates and may request data from other modules within the dyslexia test application to create associations among data using system templates. The Analysis Module may receive data from other modules and process that data to generate individual or aggregated performance metrics to be relayed to the backend intelligence through client interfaces. The Recommendation Module calculates recommended performance goals or activities for that user or group based on results of classification and analysis to be relayed to the backend intelligence. The Display Module presents a user

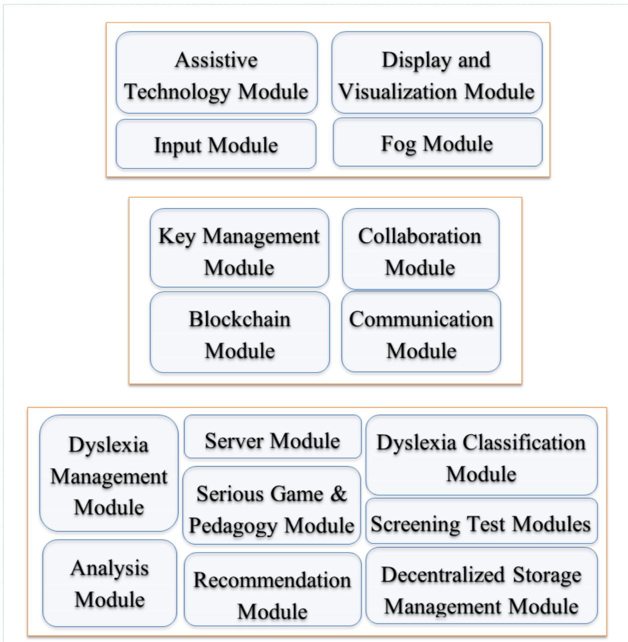

FIGURE 2. High level system use case diagram.

interface to a user to display visually the results generated by the dyslexia test application. The displayed user interface is interactive, allowing the user to view, add, edit, configure, copy, store, remove, send or comment upon displayed results. In one embodiment, automatic performance review documentation uses all of these methods.

Figure 2 also illustrates the client-side management module that manages the data acquired through user interfaces, to be collected and relayed to the backend intelligence, and the results to be saved to the Blockchain. Similarly, the management module also receives information from the backend intelligence to be displayed over user interfaces. The Communication Module uses the network resources to communicate with the MEC and backend decentralized repository over the network. The Collaboration Module maps the user to groups taking similar tests. The Server Module uses the Communication Module to reach its cohort in the backend intelligence for relaying the results. The cloud/fog management module interfaces the client side to the relational, NoSQL databases and Blockchain on the server side.

The ***Backend Intelligence*** module enables the analytic engine to do real-time and forensic analysis of the data captured from individual users regarding dyslexia. The data is analyzed for each individual, group, school and community, and common metrics are measured. An ***Expert system*** is introduced for the backend intelligence analytics to be further analyzed by experts such as doctors, as well as policymakers, for checking the higher-level value and impacts for health care.

Figure 3 shows the high-level performance metric impacts for users as individuals, teams, groups and communities at large. The proposed dyslexia management system operates on the individual performance of dyslexia test tracking

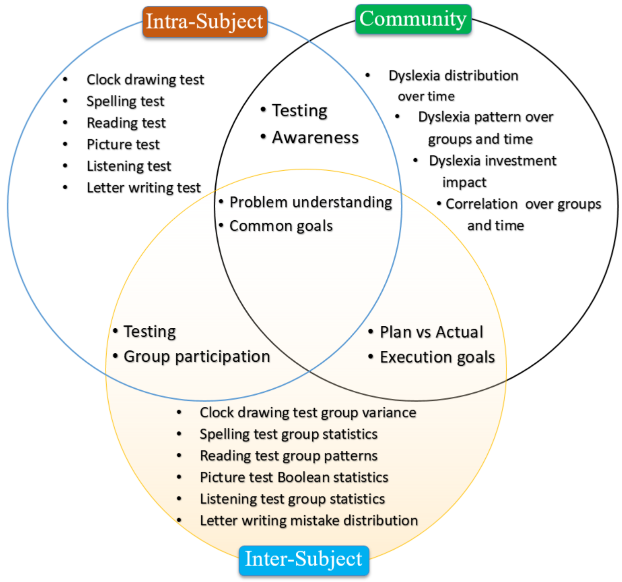

FIGURE 3. Performance metric impacts.

metrics such as the clock-drawing test, spelling test, reading test, picture test, listening test and letter-writing test. Figure 3 also shows analysis at the group level, including metrics to measure variance, group patterns, mistake distribution, and further statistics. Productivity impacts are measured at individual and group level, whereby tracking test results at individual level holistically leads to group statistics. Figure 3 also illustrates community level analysis, where metrics such as dyslexia distribution over time period, group patterns, investment impacts, correlation with various groups at various times, and time management can be tracked. In addition, metrics comparing communities can indicate potential areas for improvement, such as screening efficacy, compensation, investment and impact.

Figure 4 illustrates an embodiment where feedback is taken in real-time in a deterministic and stochastic random fashion. In another embodiment, feedback is taken non-real-time in a deterministic and random fashion, when the project test is completed. Figure 4 illustrates the different feedback types and the impact it has depending on who the feedback represents. Feedback has two types, Language and Abstract. Language test feedback is taken through the online user interface where tests concentrate on the reading, writing and spelling aspects. The individual user is tested regarding competency to properly interpret and answer the language aspects through letter writing test, spelling test and reading test. The second type of feedback is more abstract, where the test concentrates on the user's competency to listen, draw and interpret. Here the user takes a test using the online user interface comprising of a listening test, family drawing test and clock drawing test.

Figure 4 also illustrates the statistics pertaining to individual, group and community. The performance feedback for group or community is more filtered and distilled across multiple individuals. For example, the collection of individual language tests is represented at group or community level

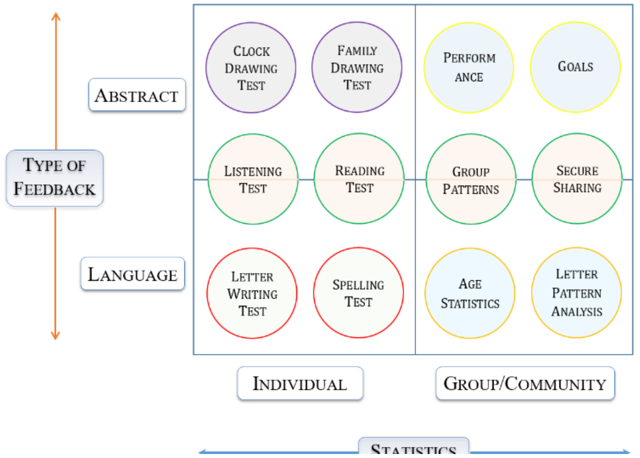

FIGURE 4. Feedback types.

through age statistics, letter pattern analysis, distributions, and other group patterns. More abstract-level feedback for groups or communities are obtained through filtered representation of results regarding test performance and goal tracking.

Figure 5 illustrates the intelligent dyslexia-analytics solution components. The users participate in the dyslexia test online. Users could be either individual or a group. The tests are administered locally first and then uploaded to the backend system online over the Internet. The test vectors are captured by the client modules and the test vectors are transferred to the analytics backend system for analysis. The information is stored in the database system. The data is open for expert analysis via the cloud-based expert system through the expert client. The results for individual, group, community and event country can then be used by policymakers and researchers.

Figure 6 illustrates the intelligent dyslexia-analytics solution components. The client side test is taken by individuals and the results are compiled for group, and community. The client side components directly communicate with the backend intelligence. The backend intelligence has abstraction for user interface, classification, synchronization layer, analysis platform, dyslexia engine, and web services layer. The backend intelligence also provides the analytics, user interface and authentication capability. The backend intelligence interfaces with the cloud-based expert system via which experts and policy-makers access the intelligence system to receive the analytical results for the performance metrics. The backend intelligence uses a redundant knowledge base to store the data.

III. IMPLEMENTATION

The four software modules were tested using a Samsung tablet, Samsung Galaxy Note 4, and a Microsoft Surface Pro 4 tablet PC with a stylus. In the tablets and smartphones, we stored images as .jpg (896∗530 resolution) and video as .mp4 format. Videos were generated via the FFMPEG codec library. A 3-minute video is typically 30-50 kilobytes

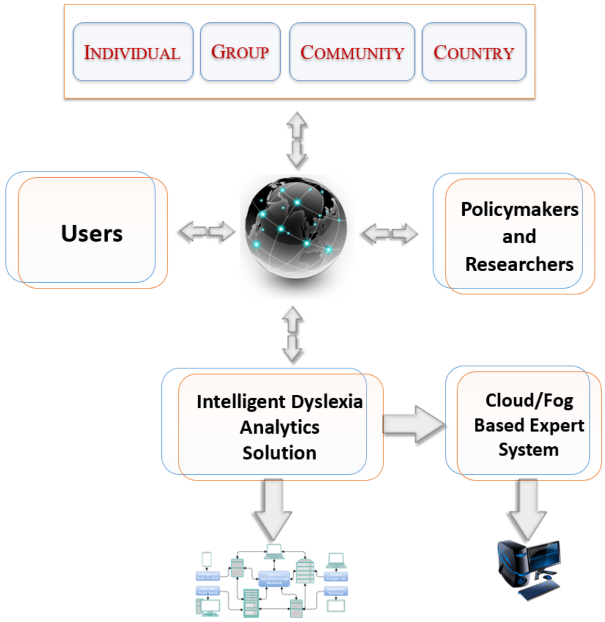

FIGURE 5. Intelligent dyslexia analytics solution architecture.

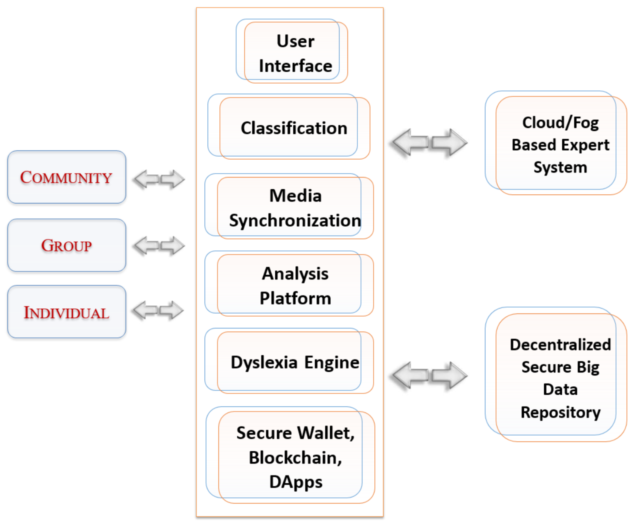

FIGURE 6. Intelligent dyslexia analytics solution components.

(at 30 FPS). Our library of collected media enables us to detect the numbers 1 to 12 drawn by the user as well as the location and angles of the clock's hour and minute hands. The library was developed by means of Python's openCV library for image processing. To detect numbers and hands we used the KNN algorithm. The library functions properly, but would benefit from further training data from actual tests to improve the accuracy of test results.

The gaze-tracking module utilized EyeTribe SDK version 0.9.56. Amazon's Infrastructure as a Service was used to store our big data. Through Amazon EC2, we are able to rapidly scale up or down according to requirements, which due to variable usage is essential for our application. We installed the API server on EC2 services and used AWS for automatic scaling and load balancing, which becomes enabled when

EC2 average utilization is low or high. Scaling uses Cloud Watch, while Elastic Load Balancing enables the distribution of traffic to auto scaling group instances to ensure optimal resource utilization and cost minimization. Amazon S3 was used to store our big data media files, and a relational PostGreSQL Database to store profiles of users, dyslexia diagnosis, test metadata, and various other data.

With respect to Blockchain, we implemented several versions to examine its feasibility, including permissioned Ethereum and Hyperledger private Blockchain. Moreover, we tested the open source bridging framework ark.io through which both Ethereum and Hyperledger chains can exchange information. The off-chain distributed storage for the multimedia therapy files were implemented using IPFS. With the help of DHT, MEC nodes can store and share big data in a decentralized way. The off-chain data can be authenticated using InterPlanetary Name Space and Blockchain. The Merkle Directed Acyclic Graph (DAG) allows the multimedia data to be uniquely stored and retrievable. A JavaScript and Node.js version of the IPFS has been implemented for the testbed. In another instance, the BigchainDB has been implemented and tested as the complimentary secure data storage for comparison. One key interesting feature of the BigchainDB is that it supports a pseudo-write capability by allowing off-chain metadata of a particular dyslexia exam session.

Figure 7 illustrates control and data flow to the user interface. The visual interface for individual users and groups captures performance, reports, events, benchmarks and activities. The data is fed as individual data, group data and community data. The individual data is received through test modules from user interfaces in client device components. The group data and community data are received through group statistics and community statistics received from the backend intelligent dyslexia analytics engine. User interface data is provided based on profiles. The data are stored in a knowledge base. The user interface also collects data through expert system analyses and the feedback based on the analyses.

Figure 8 illustrates the message sequence chart for user data flow as part of feedback gathering and analysis. A user enters the login certificates and the user interface authenticates and checks the profile. The web services layer receives the data and the authentication process is completed. The end user starts inputting the dyslexia test data, which are gathered and sent to the dyslexia backend engine, for analysis and synchronization. The data is stored in a knowledge base. The analytics metrics derived are communicated back to the visual interface.

IV. TESTING

Figure 9 illustrates the user interfaces for various modules aimed at doctors/medical experts. The user interface includes students' test results that have been automatically tagged. A color-coding system is used, whereby a red circle indicates a pattern which confirms dyslexia through auto-grading, yellow indicates possible dyslexia but requires medical

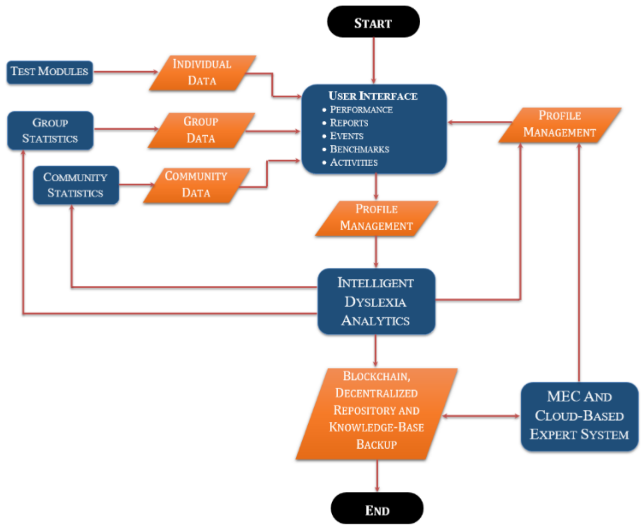

FIGURE 7. Control and data flow to user interface.

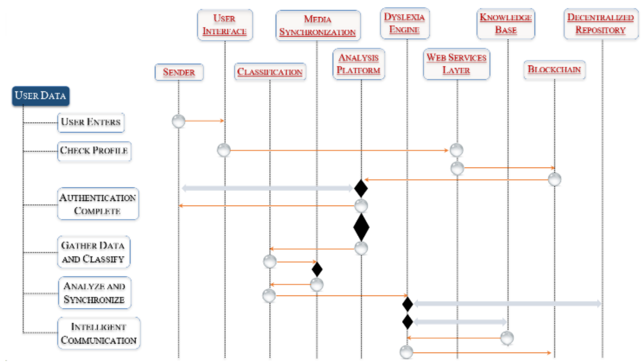

FIGURE 8. Feedback gathering & analysis.

confirmation, while green shows that the test results do not exhibit dyslexia symptoms. Such a 'traffic light' system is useful for the medical professional to obtain a quick overview of a large number of tests. Manual review of all or specific test results can be conducted by doctors to confirm dyslexia symptoms.

Figure 9 (a) illustrates a user interaction video which has been automatically graded via server side algorithms according to the positioning of clock hands, marking of hour and minute hands, and the size of arrows for hour and minute hands. The video captures the gradual drawing of the clock, helping the medical practitioner to understand how this developed over time. Figure 9 (a) synchronizes the video from the clock drawing test with eye tracking data. Patterns of eye movement, along with the development of the clock face, can help to diagnose dyslexia. Doctors may mark comments on the examined video and eye tracking data. Figure 9 (b) illustrates the test for drawing a family member, as seen by the dyslexia doctor. The data for the user, as captured by the client component, is shown in the visual interface of the doctor for further analysis.

Figure 9 (c) and (d) illustrate the writing test and the automatic marking feature, which analyses the media based

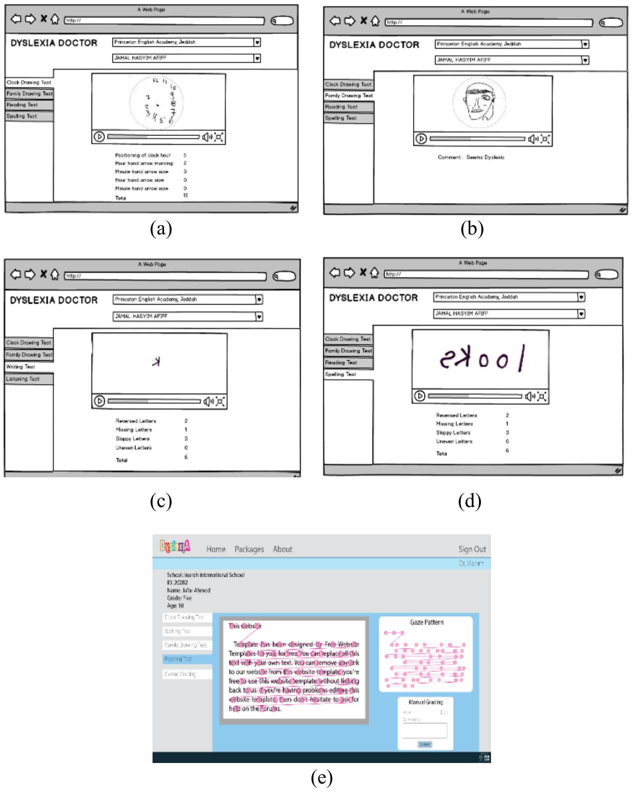

FIGURE 9. Test results visualization and authoring interface for medical doctors.

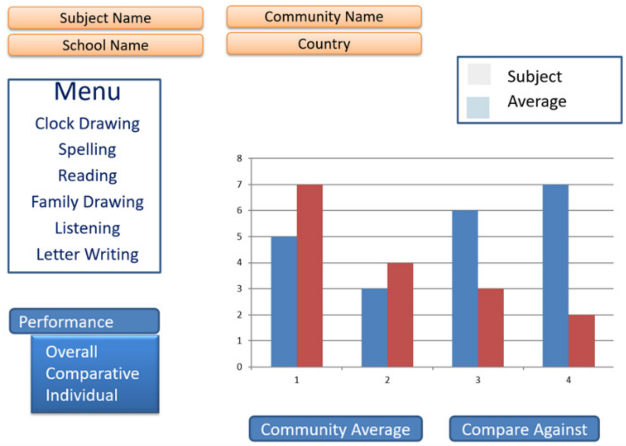

FIGURE 10. User interface for performance comparison.

on missing, reverse, uneven or sloppy letters. Figure 9 (c) illustrates the results for the letter writing test for an individual or student as captured by the client component. The data is reviewed by the doctor through the visual interface for further analysis. Figure 9 (d) illustrates the results of the listening test for of an individual or student as captured by the client component. Again, this is displayed in visual interface for further medical analysis. Figure 9 (e) shows the automatic augmentation of pupil coordinates superimposed on the reading test content in spatio-temporal dimensions, which will give a medical practitioner the movement order of the pupil. The doctor may accept the automatic grading or can manually enter their own grading for the eye movement test. Finally, Figure 9 (e) illustrates the results of the reading test for an individual. The normal pattern of pupil movement is shown and compared to the captured pupil movement for the examined user or student.

While the user reads the text, the pupil tracker reads the pupil movement co-ordinates and stores them in a temp file. Once the reading module is finished, these X, Y values are sent to the server side API. The server side API simply plots the X, Y values and creates a JPG file, which will be made available to the doctor's module (similar to the video for other three modules). Once plotted, these should appear as a continuous z pattern. Once the pupil coordinates are sent from the tablet to the server, a server function receives the Excel, CSV or JSON file, passes it to the plotting function, returns a JPG image, and then stores it in the web server folder, which is shown in the respective reading test web page in the doctor module. At this first stage, this image is not only made available for the doctor to observe manually dyslexic eye patterns, but a new audio module is also introduced, where the audio captured during the test is presented. The student looks at the text and reads it aloud (i.e. reads it loudly while tracking eye movement). At the end of the test, both pupil movement coordinates and audio are stored and made available at the server-side doctor module. The doctor now can see the pupil plot superimposed on the text he or she read and hear the audio.

Figure 9 (e) uses the following algorithm for the reading module:

1. The user chooses the reading module and language.
2. The timer starts counting T minutes.
3. The user starts reading text by eye loudly using voice from left (non-Arabic) or from right (Arabic).

   i) The *CaptureVoice* function captures the audio stream and stores it in a temporary file.

   ii) The *CapturePupilCoordinate* function captures pupil coordinates and stores them in a temporary file.

   iii) A timer and normalized aspect ratio is used to synchronize the reading text location and pupil movement, making them augmentable and enabling pupil coordinates to be superimposed on top of the text.
4. The user clicks on 'done' or the timer expires.
5. A session multimedia file along with the user profile is created that contains the synchronized text, audio and pupil movement data, which is ready for uploading to the server.
6. The multimedia payload is uploaded to the decentralized repository, the hash of the media files and the final test results are stored in the Blockchain.

Figure 10 illustrates an embodiment of the data analytics and statistics visualization. The granularity of the data is at patient, school, community or country level. The time period of the analysis is entered for analytics. The comparison can be done between patient/user and the average group as a graph. The menu can be used to specify the metric that needs to be compared. Performance can be measured at either

TABLE 1. Auto grading metrics.

Name of the Test	Name of Extracted Feature	No. of Test Instances	No. of Correctly Recognized Instances
Clock drawing	Positioning of Clock Hour	200	189
	Hour Hand arrow marking		187
	Minute Hand arrow size		182
	Hour Hand arrow size		178
	Minute Hand arrow size		181
Family drawing	Pupil and iris		165
	Eye brow present		175
	Forehead and hair		191
	Lips, nostril, chin, mouth and jaw		156
Writing/ Reading /Spelling	Reversed letters		191
	Missing letters		197
	Sloppy letters		183
	Uneven letters		188

TABLE 2. Screening test data uploading delay.

Name of the Test	No. of Test Instances	Average Delay (seconds)
Clock drawing	200	14.775
Family drawing		15.343
Writing/ Reading /Spelling		13.385

overall country level, group level or individual level for mean analysis.

Table 1 shows the recognition rate of different dyslexic patterns. More than 10 healthy subjects and 5 dyslexic patients were invited to sit the test modules for 200 instances of the test modules at different temporal dimensions. The healthy subjects were shown the dyslexic patterns and were told to simulate the dyslexic symptoms, to check the recognition rate of the auto-grading algorithms. As seen from Table 1, the more detailed and low-level the features are, and the more diversified the feature can be, the poorer the recognition rate. Nevertheless, in the first phase, the auto-grading feature is used to filter out dyslexic subjects at a certain threshold level and to tag a set of subjects from among a very large number of subjects so that the medical analyst can look at the test results manually in the second phase.

We have calculated the average delay shown in Table 2 as follows:

Average test module uploading time to the decentralized cloud and MEC node = processing delay (at smartphone or tab environment) + upstream network delay (at client) + processing delay (at decentralized edge node) + upstream network delay (at edge) + processing delay (at the cloud to perform auto-grading and adding results to Blockchain and off-chain).

As shown in Table 2, the average time to upload each test module is around 14 seconds, which is based on 200 instances of test modules. Since the dyslexia screening test results are not demanded for real-time applications, rather the test results follow a process of further investigation by a practitioner doctor analyzer, this delay is assumed to be acceptable. However, in our future endeavor, we will do more research to lower the delay. We will also make more testing as per medical benchmarks to make it deployable in clinical environments.

V. CONCLUSION

This paper has presented a novel, language-independent mass screening mobile health framework aided by auto-grading algorithms to recommend the classification of dyslexic subjects. Dyslexia diagnosis data can be shared securely with mobile medical practitioners around the globe. We use Blockchain to store test results to make them immutable and securely shareable with a number of stakeholders. Different clinically approved test modules have been developed and tested by medical doctors who treat dyslexic patients. Regarding future work, we intend to deploy our framework in different hospitals in the UK and Saudi Arabia for further clinical trials. As for the future work, we will also investigate better recognition and auto-grading algorithms to increase the rate of dyslexic pattern recognition and decrease the delay in uploading the test modules.

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MD. ABDUR RAHMAN is currently an Assistant Professor and the Chairman with the Department of Forensic Computing and Cyber Security, University of Prince Mugrin, Madinah, Saudi Arabia. He has authored over 100 publications, including refereed IEEE/ACM/Springer/Elsevier journals, conference papers, and book chapters. He holds five U.S. patents. His research interests include serious games, cloud and multimedia for healthcare, IoT, smart city, secure systems, multimedia big data, and next-generation media.

ELHAM HASSANAIN has served as the Vice Dean of the College of Computer and Information Systems, Umm Al-Qura University. She has also served as a member of Saudi Parliament for a duration of 4 years. She is currently an Assistant Professor with the Department of Forensic Computing and Cyber Security, University of Prince Mugrin, Madinah, Saudi Arabia, where she is also the Deputy Rector for Academic Affairs. Her research interests include e-Health, cloud and multimedia for healthcare, IoT, and smart city. She has publications in refereed IEEE/ACM journals and conferences. Recently, she has been awarded one U.S. patent on vision therapy. She has served as a member of the organizing and technical committees of several workshops.

MD. MAMUNUR RASHID received the Ph.D. degree from Cranfield University. He was with the Physics Department, Imperial College London, for three years. He was a Scientific Research Computing Specialist for three years with the Department of Engineering Science, University of Oxford. He is currently a Senior Research Fellow at the King's Business School, King's College London. He is also with a leading digital analytics centre called Consumer and Organizational Digital Analytics Research Centre (CODA). He is currently involved in solving the diverse set of problems for finding impacts of state-of-the-art technology in the area of IoT, big data, blockchain, pattern recognition, smart infrastructure, future cities, and distributed HPC. He was a recipient of the Ph.D. Scholarship to work at the European Organisation for Nuclear Research, Switzerland, after he started his Ph.D. degree.

STUART J. BARNES has been holding chair positions at other universities since 2005. He joined King's College London in 2015, where he is currently a Chaired Professor and the Director of the Centre for Consumer and Organisational Digital Analytics, King's Business School. A polymath, he is opposed to disciplinary silos and enjoys working across a number of academic disciplines. His recent research projects have focused on sharing economy, social media, big data, mobile communications, virtual reality, and virtual worlds. He has published five books (one a bestseller for Butterworth-Heinemann) and over 150 articles in leading outlets. He reviews for many leading research grant bodies and journals, is an Associate Editor of *Information and Management*, and has been a programme committee member or a track chair for over 50 academic conferences.

M. SHAMIM HOSSAIN (SM'09) received the Ph.D. degree in electrical and computer engineering from the University of Ottawa, Canada. He is currently a Professor with the Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia. He is also an Adjunct Professor with the School of Electrical Engineering and Computer Science, University of Ottawa. He has authored and co-authored about 200 publications, including refereed journals, conference papers, books, and book chapters. Recently, his publication is recognized as the ESI Highly Cited Paper. His research interests include cloud networking, smart environment (smart city, smart health), social media, IoT, edge computing and multimedia for health care, deep learning approach to multimedia processing, and multimedia big data. He is a Senior Member of the ACM. He has served as a member of the organizing and technical committees of several international conferences and workshops. He was a recipient of a number of awards, including the Best Conference Paper Award and the 2016 *ACM Transactions on Multimedia Computing, Communications, and Applications* Nicolas D. Georganas Best Paper Award, and the Research in Excellence Award from the College of Computer and Information Sciences, King Saud University (three times in a row). He has served as a co-chair, a general chair, a workshop chair, a publication chair, and on TPC for over 12 IEEE and ACM conferences and workshops. He is currently a Co-Chair of the First IEEE ICME Workshop on Multimedia Services and Tools for Smart-Health (2018). He served as a Guest Editor of the *IEEE Communications Magazine*, the IEEE Journal of Biomedical and Health Informatics, the IEEE Transactions on Cloud Computing, the *International Journal of Multimedia Tools and Applications* (Springer), *Cluster Computing* (Springer), *Future Generation Computer Systems* (Elsevier), *Computers and Electrical Engineering* (Elsevier), *Sensors* (MDPI), and the *International Journal of Distributed Sensor Networks*. He is on the Editorial Board of the IEEE Network, *the* IEEE Multimedia, and the IEEE Access, the *Journal of Network and Computer Applications* (Elsevier), *Computers and Electrical Engineering* (Elsevier), *Human-centric Computing and Information Sciences* (Springer), *Games for Health Journal*, and the *International Journal of Multimedia Tools and Applications* (Springer). He also serves as a Lead Guest Editor of the IEEE Network, *Future Generation Computer Systems* (Elsevier), and the IEEE Access.