Towards an On-line Handwriting Recognition Interface for Health Service Providers using Electronic Medical Records

Viktor Mikhael M. Dela Cruz, Christian E. Pulmano and Ma. Regina Justina E. Estuar
Ateneo de Manila Univeristy, Katipunan Avenue, Quezon City, Metro Manila, Philippines

Keywords: Electronic Health Records, Handwriting Recognition, Health Informatics, Usability.

Abstract: The 2019 Universal Health Care Act in the Philippines has allowed healthcare service providers to have a second look at using electronic medical records (EMRs) in their practice with tools that enable servicing the poorest of the poor and coursing payments via EMR. A review of first world country narratives, however, show evidence of the substandard usability of EMRs. Physician work is impeded as almost two-thirds of consultation time is spent documenting on an EMR instead conversing with patients face-to-face. This paper describes a handwriting recognition interface for EMR data entry that is user-friendly and is unobstructive to the patient-physician relationship. An initial prototype tested by medical students showed a handwriting recognition accuracy of 34% while a second testing by health service providers showed a handwriting recognition accuracy of 42%. Findings show that recognition is challenged by specialized words and accidental markings which cause extra spaces and extra symbols. Additional features to the system as well as possible augmentations to improve accuracy and efficiency through ontology, machine learning, and AI are also roadmapped.

1 INTRODUCTION

The promulgation of the 2019 Universal Health Care Act (UHC) in the Philippines ushers a new era of health care in the country (Congress of the Philippines, 2018). In line with leveraging the latest in health technology to facilitate efficient health services delivery, section 36 of the Universal Health Care Act requires health service providers and insurers to utilize the electronic health record (EHR), interchangeably referred to as electronic medical record (EMR) (Congress of the Philippines, 2018).

An EMR is an electronic record of an individual's health-related information that can be managed by official clinicians and staff of a health care organization (Horowitz et al., 2008). It contains patient information such as diagnoses, medicines, tests, allergies, immunizations, and treatment plans (National Cancer Institute, 2019). Physicians are able to access core functions such as viewing, documentation and care management, ordering, messaging, analysis and reporting, patient-directed functionality, and billing through EMRs (Smelcer et al., 2009).

Barriers such as high initial financial costs, slow and uncertain financial payoffs, and high initial physician time costs deter medical practitioners from utilizing EMRs (Miller and Sim, 2004) despite EMRs providing many benefits (Hillestad et al., 2005; Menachemi and Collum, 2011; Ben-Assuli et al., 2013; Blumenthal and Glaser, 2007) and being implemented on a global scale (McConnell, 2004). One underlying cause of barriers to using EMRs is their poor usability as most EMRs are not intuitive and have interfaces that are not user-friendly (Miller and Sim, 2004; Smelcer et al., 2009; Belden et al., 2009; Hill Jr et al., 2013). Almost 3 in every 4 physicians agree that EMRs contribute great stress that leads to burnout. However, studies show that this stress can be greatly reduced by improving user interfaces and including the users into the system design process (Stanford Medicine, 2018; Gardner et al., 2018).

A solution that may improve the usability of EMRs, decrease the time spent by physicians encoding in EMRs, and ultimately increase adoption and usage rate of EMRs is by giving physicians the ability to manually scribe their patient encounter during consultation. Most EMRs only allow free-text typing as an off-the-shelf way of data entry but many physicians still prefer to write (Smelcer et al., 2009; Tsoromokos et al., 2017; Arvary, 2002). Additionally, electronic charting can take up to 238.4% longer than manually writing on paper (Hill Jr et al., 2013; Poissant et al., 2005). It makes sense, therefore, to integrate handwriting recognition as an out-of-the-box functionality

Dela Cruz, V., Pulmano, C. and Estuar, M.
Towards an On-line Handwriting Recognition Interface for Health Service Providers using Electronic Medical Records.
DOI: 10.5220/0008944403830390
In *Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2020) - Volume 5: HEALTHINF*, pages 383-390
ISBN: 978-989-758-398-8; ISSN: 2184-4305

to modern EMRs as a way of unobtrusively replacing old-fashioned paper charting without adding the extra time taken to type nor the hassle of changing already successful habituated workflow.

While handwriting recognition systems for medicine have been implemented (Kumar et al., 2016; Roy et al., 2017a; Roy et al., 2017b), only few are concerned with on-line handwriting recognition (Chen et al., 2010; Bandyopadhyay and Mukherjee, 2014; Holzinger et al., 2010). These systems, albeit innovative and aim to contribute positively, may still cause stress and prove to be counterproductive without proper user feedback and assessment. This paper describes a more user-friendly, less time-consuming, and more usable means of data entry for EMRs through a handwriting recognition interface that is designed for the physician. The approach involves utilizing open-source technologies and implementing hardware-agnosticism to open possibilities for low cost deployment of the solution. Furthermore, iterative development phases are practiced to ensure proper incorporation of the user in the design process.

The rest of the paper reports prototype initial results and findings as well as additional features and possible augmentations that will be done in next iterations in order to improve handwriting recognition accuracy and efficiency, and EMR usability.

2 HANDWRITING RECOGNITION IN MEDICAL CONTEXT

Innovative solutions to cumbersome data entry in the field of health are speech and handwriting recognition. In the case of the latter, there have been various attempts to explore the subject matter and either develop new software or optimize currently existing solutions.

A survey was conducted to determine interest in handwriting applications for EMRs (Arvary, 2002). The survey was distributed over 411 primary care physicians (PCPs) and garnered a total of 156 responses. The survey showed that 78% of the respondents agreed that digital ink would be a useful supplement to EMRs. Furthermore, no subgroup showed less than 73% support for handwriting implementations on EMRs.

The DPP4BIT application is a web-based technology that allows editing, management, import, and export of any document in digital form created for the purpose of digital recording and handling of medical equipment (Tsoromokos et al., 2017). Using Anoto's digital pen, DPP4BIT is able to perform on-line handwriting recognition on digital forms that are managed by Health Care Units. A pilot test showed that 90% of nursing staff found the setup absolutely user-friendly, 85% of users felt more confident using the digital pen, and work efficiency and speed was highly improved.

One study proposed improving the recognition component by incorporating medical knowledge into the recognizer (Chen et al., 2010). This integration provided a 5% increase in accuracy of recognition from a ”BestConfidence” module that selects word candidates with the highest confidence (Chen et al., 2010). This was achieved by augmenting the post-processing phase of recognition on a semantic level with a medical knowledge model.

Another study developed an on-line handwriting recognition system that recognizes India's second most used language, Bengali, or Bangla, for the purpose of web-based telemedicine in rural medical centers (Bandyopadhyay and Mukherjee, 2014). This paved the way for low-cost, virtual medical consultations between doctors and remote patients where physical visits were either not needed or impossible (Bandyopadhyay and Mukherjee, 2014). This was achieved by utilizing shape-based features and employing pattern recognition techniques.

It is noteworthy that these studies have been implemented in health systems in parts of the world such as the United States, India, and Germany, and it can be safely presumed that there are many more of the same in other nations. This further strengthens the need for an efficient, effective, and satisfactory health system within the Philippines.

3 PROTOTYPE IMPLEMENTATION

On-line handwriting recognition involves accepting handwriting input from a digital surface, analyzing factors such as upward and downward strokes as well as spaces and time from pen up and pen down, and then processing the input in order to classify which characters or words the input approximates to.

For this purpose, the graphical library MyScriptJS was used (MyScript, 2019). MyScriptJS is a JavaScript library that can be used in any web application to bring handwriting recognition.

Handwriting recognition is requested by supplying user-correspondent application keys and a preferred language to the appropriate API URL. This request is sent to the MyScriptJS server for processing by their recognizer. MyScript performs three key processes simultaneously in order to find the closest recognition result. These processes are symbol classification, segmentation, and linguistic-based analysis. The finished result is sent back to the client in MyScript's JSON Interactive Ink eXchange (JIIX) format.

Figure 1 illustrates a simple implementation of the handwriting interface using MyScriptJS written in JavaScript as accessed on a desktop PC. Users are greeted with a generous writing area and a text field that shows the corresponding word recognition of what they write after scribing.

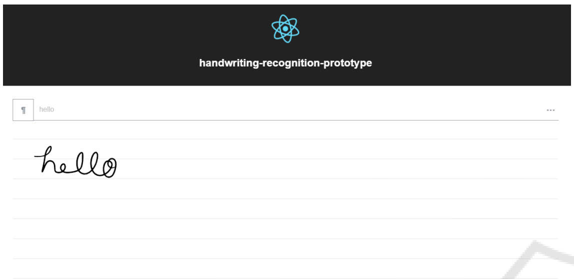

Figure 1: MyScript implementation prototype accessed on a desktop PC.

The interface was deployed on a private server using Google services as a means of testing and prototyping. Current features of the prototype include a full-fledged handwriting recognition module, input fields for correct text translations and optional identifiers, and the option to either export data locally or to a private cloud database. The basic flow of a test is depicted in Figure 2.

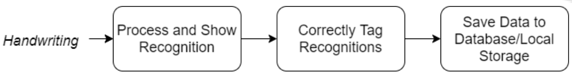

Figure 2: Flow of tasks during a prototype test.

4 RESULTS, DISCUSSION, AND RESEARCH ROADMAP

4.1 Local Experiment

As an initial evaluation of the prototype's capabilities, students in their 3rd year of studying medicine in the Philippines were asked to write down 5 common words used or written by physicians during consultations. The students were given the choice of using the prototype on a PC or on a mobile device. After their testing, the students were asked to take note of the words they wrote and what were actually recognized.

Figure 3 illustrates a sample use case of the prototype. The 10 students who participated in the testing were able to produce a total of 50 samples which were manually categorized into four classifications: accurate, wrong, "with extra characters", and "with extra spaces". From the 50 samples, the prototype was able to achieve an accuracy of 34%. Breaking the numbers down, the prototype was able to get 17 out of 50 recognitions correct while it got 16 out of 50 recognitions wrong. Furthermore, 10 out of 50 recognitions, albeit correct, were padded with extra characters and 7 out 50 recognitions, even though correct, were padded with extra spaces.

Three students used the prototype on a PC while the other seven tested it on a mobile device. However, this was not enough to produce significantly different results. Those who used PCs with the mouse to write were able to get similar results as those who used mobile devices with fingers to write.

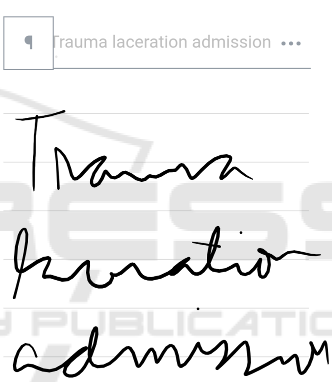

Figure 3: Sample handwriting test case.

After further observation of the local experiment handwriting samples, some conjectures made to explain the errors include accidental markings such as can be seen in the bottom left of Figure 4, slant handwriting direction such as in the case of Figure 5, and poor recognition handling of the letter "i" such as in the case of Figure 6 which shows overemphasized superscript dots on the letter i's. With these in mind, punctuation marks with dots such as the question mark (?) and the exclamation point (!) may cause problems with recognition. Additionally, words written on an unequal number of lines may also challenge the handwriting recognition.

4.2 Real-world Scenario Experiment

In an attempt to gather data from real-world scenarios, a second testing of the prototype was conducted by health professionals during a series of clinic visits.

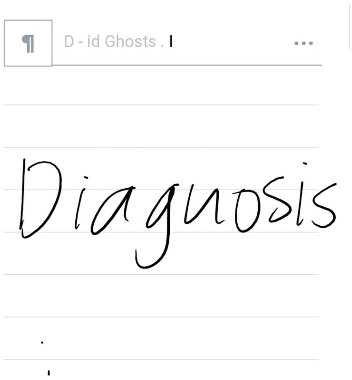

Figure 4: Handwriting test case with wrong recognition due to accidental marking.

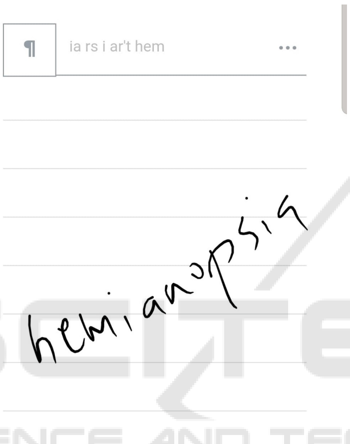

Figure 5: Handwriting test case with wrong recognition due to slant handwriting.

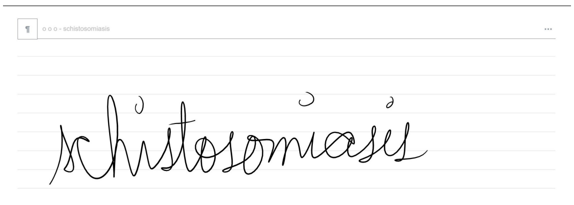

Figure 6: Handwriting test case with wrong recognition due to overemphasized superscript dots.

Participants were composed of allied health professionals working in health establishments based in the Western Visayas region of Philippines. A total of 15 clinics were visited and 9 respondents agreed to test, 2 of which were nurses, 3 were midwives, and 4 were doctors.

Participants of the test were asked to write a random first name, a random diagnosis, and a random prescription. The first case was to assess the prototype's name recognition, while the second case was to assess the extent of medical-related terms the prototype can recognize, and the last case was to assess the prototype's number and symbol recognition. Moreover, the participants were asked to write with their pointer finger on a mobile phone sporting a 6.2 inch display which effectively provided a writing surface that was 4.5 inches in width and 2 inches in height at any given time.

Data gathered included the correct words, the actual recognized words, and the respective stroke objects that composed each test. Upon test completion, data collected was sent to a private database for storage and further analysis.

Script and cursive handwriting styles were the two handwriting styles observed where script was used generally while cursive was used only by doctors. Figures 7 and 8 illustrate good representatives of the general look of the received script and cursive handwriting samples.

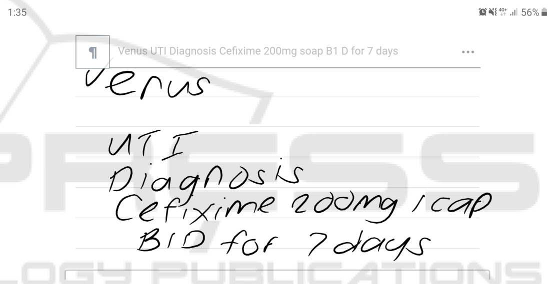

Figure 7: Sample test case written in script.

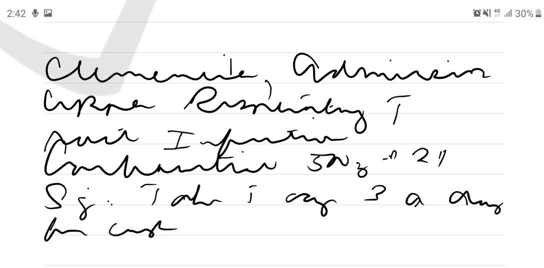

Figure 8: Sample test case written in cursive.

The 9 respondents were able to produce a total of 27 phrases (9 names, 9 diagnoses, 9 prescriptions) that comprised of 100 words. For the second testing, the prototype was able to achieve an overall accuracy of 42% where accurate means perfect recognition including capitalization. Further analysis showed that the prototype was able to achieve an accuracy of 55% with names, 38% with diagnoses, and 0% with prescriptions. Additionally, an accuracy of 48% and 29%

on script and cursive handwriting styles respectively were also achieved. However, extra characters and extra spaces occurred more frequently in this round of testing compared to the first testing.

In the case of names, it was observed that common names were easily recognized but more unique ones challenged the prototype. Moreover, in the case of diagnoses, disregarding less detailed handwriting, the prototype was able to recognize those composed of common words such as ”Upper Respiratory Tract Infection” and ”Dengue Fever” but had difficulties with specialized ones such as ”Tonsillopharyngitis”. Furthermore, in the case of prescriptions, the prototype performed poorly in recognizing symbols such as the number sign (#), abbreviations such as ”BID” or ”sig”, and numbers that were less defined such as the ”500” depicted in Figure 8.

4.3 Research Roadmap

The next steps involves exploring ways to improve the current handwriting recognition implementation. Two possible augmentations may be integrating medical ontologies for word suggestions and comparing recognitions to a local best approximate for word correction. These, as well as other additions, will be further explicated in the succeeding sections.

At the end state of research, EMR data entry will then only follow a simple 3-step process: (1) a physician writes down notes on the interface during consultation, (2) the interface processes handwriting input and trains itself, and (3) the interface extracts and automatically maps key clinical text to their respective EMR fields. Figure 9 outlines the process flow once all features have been studied and implemented.

4.3.1 Medical Ontologies for Word Suggestion

A novel attempt in aiding handwriting recognition is by introducing an artificial intelligence that searches a medical ontology for related concepts that may augment the current text input written by the user. A medical ontology is a model of the knowledge from a clinical domain (Jovic et al., 2007). It contains all of the relevant concepts related to the diagnostics, treatment, clinical procedures and patient data. Essentially, ontologies are designed in a way that allows fluid knowledge inference and reasoning. This may allow the handwriting recognition to provide quick text correction and beneficial word suggestions as users scribe.

While medical ontologies have been extensively studied and have been proven to be beneficial (Zaman et al., 2017; Mate et al., 2015; Cases et al., 2014; Washington et al., 2009; Sarntivijai et al., 2016; Maarouf et al., 2017; Scheuermann et al., 2009), the application of these has yet been explored in the context of text correction and word suggestion for medical handwriting recognition systems. Medical ontologies used in the previous studies include the Human Phenotype Ontology (HPO) (Robinson et al., 2008) and the Ontology for General Medical Science (OGMS) (Scheuermann et al., 2009). The OGMS will serve as the pilot medical ontology utilized in the continuation of this study.

The OGMS is a framework of terms that encompasses the field of diseases, from causes and manifestations to diagnostic acts, as recognized and interpreted in the clinic (Scheuermann et al., 2009). It includes very general terms used in the clinical settings such as ”patient”, ”diagnosis”, and ”disease”. This will provide the handwriting recognition interface a good backbone for ontological text input augmentation.

4.3.2 Local Best Approximate for Correction

MyScriptJS uses Interactive Ink in order to processes user input in real time (MyScript, 2019). Through Interactive Ink, given some handwriting, MyScriptJS is able to transform each character into a stroke object which includes an array of x and y's which are the current coordinates of the pointer on the surface, an array of t's which is the current timestamp of the pointer event, an array of p's which is the current pressure information associated to the event, and a *pointerId* which is an identifier for the current pointer. Each of the properties are recorded per unit of time until all strokes are finished.

An attempt in improving the accuracy of the handwriting recognition can be made by adding a function that compares the MyScriptJS text translation to a best approximate recognition from a local knowledge base. The local knowledge base contains previous strokes and their corresponding text translations. This will be built using data structures such as arrays and objects using JavaScript but is still subject to change once efficiency comparisons have been made with data structure implementations from other program languages.

The proposed process is depicted in Figure 10. Strokes will simultaneously be processed by the MyScriptJS server and by the local knowledge base. The local knowledge base will check for an entry that closely matches the current strokes. If there is a match, the match will be offered to the user as a suggestion. The user can then decide if the best approximate from the local knowledge base is better than the MyScriptJS text translation by either keeping the current translation or selecting the suggestion. The record is updated in the knowledge base or is added

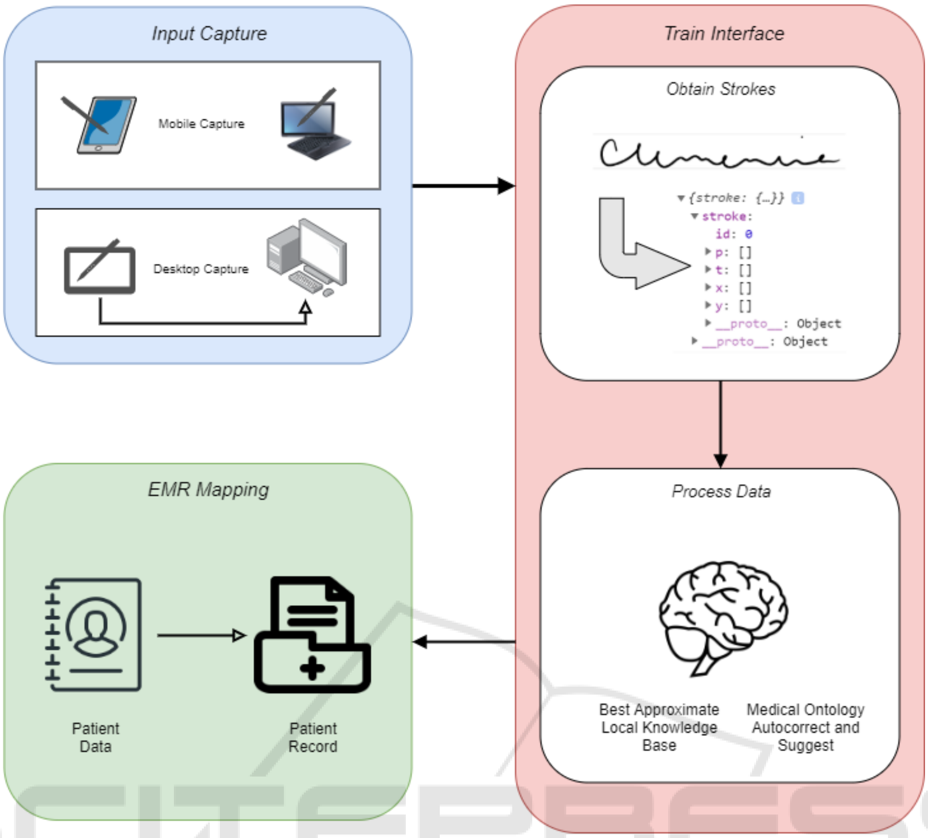

Figure 9: Goal process flow following simple 3-step EMR data entry.

to the knowledge base if it does not currently exist.

Through this, the knowledge base can learn over time as more strokes are recorded along with their corresponding user-selected correct text. Additionally, the handwriting recognition interface will be able to give out more accurate suggestions. It is possible to look at superseding the MyScriptJS text translations with the local best approximates once a high-enough confidence level is achieved.

4.3.3 Clinical Text Extraction

Once the handwriting input has been converted, the resulting plain text is fed into a clinical text analyzer to be able to filter only the words, phrases, and sentences that are important for the EMR to store. For this purpose, the natural language processing system cTAKES will be used (Savova et al., 2010). Developed by the Mayo Clinic, cTAKES is an open-source NLP system that allows the extraction of information from clinical free-text. cTAKES prides itself in being powerful, fast, scalable, modular, portable, and free. Some of what it can do with clinical texts are event discovery, negation and uncertainty detection, time expression discovery, as well as detect certain keywords that fall under a certain Unified Medical Language System (UMLS) classification.

4.3.4 Integration within an EMR

SHINEOS+ is a web and mobile-based system that aims to address the data management needs of doctors, nurses, midwives, and other allied health professionals in the Philippines (The Secured Health Information Network Exchange, 2019). The SHINEOS+ EMR service sports a number of features such as patient profiling and consultation recording, internetwork referral, automated reminders, and ePrescriptions.

Within SHINEOS+, physicians are able to create profiles for their patients as well as add consultation entries for them. A patient record contains basic information such as name, gender, age, birthday, and record location. Consultation data includes complaints and vitals and physicals at time of consultation.

After filtering the text from the handwriting interface and extracting key clinical text, the resulting set

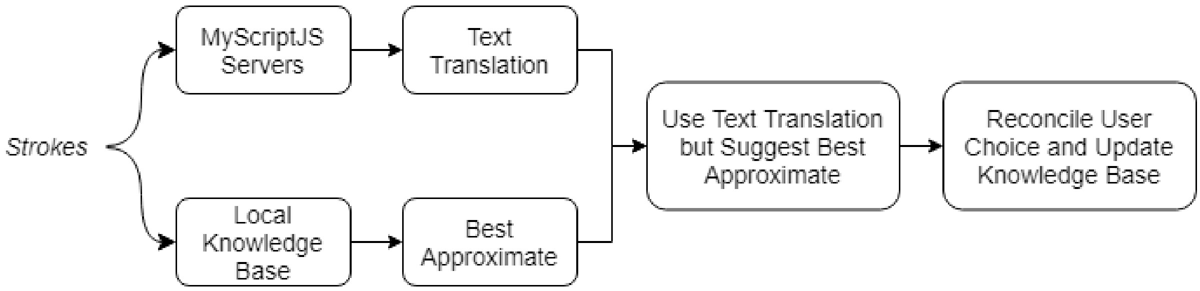

Figure 10: Methodology for accuracy improvement.

of strings will be automatically mapped to their corresponding fields in the SHINEOS+ EMR service, creating a seamless transition from handwritten script to digitized text without breaking natural workflow.

5 CONCLUSIONS

This paper looked into the poor usability of modern-day EMRs and described a handwriting recognition interface that captures physician handwriting in real-time and converts the digital input into plain text. The interface was tested by various health practitioners and the results were reported. Future additions to greatly extend the interface's functionality, practicality, and usability were also discussed.

The Universal Healthcare Act in the Philippines is changing the nation's healthcare landscape. With the UHC in play, EMRs are now at the forefront of health services. However, as beneficial as EMRs are, the rapid advancement of technology has changed their requirement from being functional to being usable. Inefficient and unwieldy health systems cannot be tolerated in today's fast moving world where patients come by the dozens. It is in the best interest of this research that physicians are given the proper tools to use so that they can worry less about compliance and focus more on tending to others. A handwriting recognition interface that can serve as a plug-in to existing EMRs hopes to be beneficial in providing a seamless interface in doctor-patient interaction.

ACKNOWLEDGEMENTS

The researchers would like to thank the Ateneo School of Science and Engineering as well as the Department of Science and Technology for subsidizing this study through the SOSE Industry Grant and the DOST-ERDT grant respectively. Additionally, the researchers would also like to thank the Ateneo Center for Computing Competency Research (ACCCRE) for their support.

REFERENCES

Arvary, G. (2002). A primary care physician perspective survey on the limited use of handwriting and pen computing in the electronic medical record. *Journal of Innovation in Health Informatics*, 10(3):161–172.

Bandyopadhyay, A. and Mukherjee, B. (2014). Web based bangla online handwritten prescription system for telemedicine through multimedia conferencing. *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, 3(12).

Belden, J. L., Grayson, R., and Barnes, J. (2009). Defining and testing emr usability: Principles and proposed methods of emr usability evaluation and rating. Technical report, Healthcare Information and Management Systems Society (HIMSS).

Ben-Assuli, O., Shabtai, I., and Leshno, M. (2013). The impact of ehr and hie on reducing avoidable admissions: controlling main differential diagnoses. *BMC Medical Informatics and Decision Making*, 13(1):49.

Blumenthal, D. and Glaser, J. P. (2007). Information technology comes to medicine.

Cases, M., Briggs, K., Steger-Hartmann, T., Pognan, F., Marc, P., Kleinöder, T., Schwab, C., Pastor, M., Wichard, J., and Sanz, F. (2014). The etox data-sharing project to advance in silico drug-induced toxicity prediction. *International journal of molecular sciences*, 15(11):21136–21154.

Chen, Q., Gong, T., Li, L., Tan, C. L., and Pang, B. C. (2010). A medical knowledge based postprocessing approach for doctor's handwriting recognition. In *2010 12th International Conference on Frontiers in Handwriting Recognition*, pages 45–50. IEEE.

Congress of the Philippines (2018). An act instituting universal health care for all filipinos, prescribing reforms in the health care system, and appropriating funds therefor.

Gardner, R. L., Cooper, E., Haskell, J., Harris, D. A., Poplau, S., Kroth, P. J., and Linzer, M. (2018). Physician stress and burnout: the impact of health information technology. *Journal of the American Medical Informatics Association*, 26(2):106–114.

Hill Jr, R. G., Sears, L. M., and Melanson, S. W. (2013). 4000 clicks: a productivity analysis of electronic medical records in a community hospital ed. *The American journal of emergency medicine*, 31(11):1591–1594.

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., and Taylor, R. (2005). Can electronic medical record systems transform health care? potential health benefits, savings, and costs. *Health affairs*, 24(5):1103–1117.

Holzinger, A., Schl¨ogl, M., Peischl, B., and Debevc, M. (2010). Optimization of a handwriting recognition algorithm for a mobile enterprise health information system on the basis of real-life usability research. In *International Conference on E-Business and Telecommunications*, pages 97–111. Springer.

Horowitz, J., Mon, D., Bernstein, B., and Bell, K. (2008). Defining key health information technology terms. *Department of Health and Human Services, Office of the National Coordinator for Health Information Technology*.

Jovic, A., Prcela, M., and Gamberger, D. (2007). Ontologies in medical knowledge representation. In *2007 29th International Conference on Information Technology Interfaces*, pages 535–540. IEEE.

Kumar, S., Sahu, N., Deep, A., Gavel, K., and Ghost, R. (2016). Offline handwriting character recognition (for use of medical purpose) using neural network.

Maarouf, H., Taboada, M., Rodriguez, H., Arias, M., Sesar, Á., and Sobrido, M. J. (2017). An ontology-aware integration of clinical models, terminologies and guidelines: an exploratory study of the scale for the assessment and rating of ataxia (sara). *BMC medical informatics and decision making*, 17(1):159.

Mate, S., Köpcke, F., Toddenroth, D., Martin, M., Prokosch, H.-U., Bürkle, T., and Ganslandt, T. (2015). Ontology-based data integration between clinical and research systems. *PloS one*, 10(1):e0116656.

McConnell, H. (2004). International efforts in implementing national health information infrastructure and electronic health records. *World hospitals and health services: the official journal of the International Hospital Federation*, 40(1):33–7.

Menachemi, N. and Collum, T. H. (2011). Benefits and drawbacks of electronic health record systems. *Risk management and healthcare policy*, 4:47.

Miller, R. H. and Sim, I. (2004). Physicians' use of electronic medical records: barriers and solutions. *Health affairs*, 23(2):116–126.

MyScript (2019). About myscriptjs.

National Cancer Institute (2019). Definition of electronic medical record.

Poissant, L., Pereira, J., Tamblyn, R., and Kawasumi, Y. (2005). The Impact of Electronic Health Records on Time Efficiency of Physicians and Nurses: A Systematic Review. *Journal of the American Medical Informatics Association*, 12(5):505–516.

Robinson, P. N., Köhler, S., Bauer, S., Seelow, D., Horn, D., and Mundlos, S. (2008). The human phenotype ontology: a tool for annotating and analyzing human hereditary disease. *The American Journal of Human Genetics*, 83(5):610–615.

Roy, P. P., Bhunia, A. K., Das, A., Dhar, P., and Pal, U. (2017a). Keyword spotting in doctor's handwriting on medical prescriptions. *Expert Systems with Applications*, 76:113–128.

Roy, P. P., Bhunia, A. K., Das, A., Dhar, P., and Pal, U. (2017b). Keyword spotting in doctor's handwriting on medical prescriptions. *Expert Systems with Applications*, 76:113–128.

Sarntivijai, S., Vasant, D., Jupp, S., Saunders, G., Bento, A. P., Gonzalez, D., Betts, J., Hasan, S., Koscielny, G., Dunham, I., et al. (2016). Linking rare and common disease: mapping clinical disease-phenotypes to ontologies in therapeutic target validation. *Journal of biomedical semantics*, 7(1):8.

Savova, G. K., Masanz, J. J., Ogren, P. V., Zheng, J., Sohn, S., Kipper-Schuler, K. C., and Chute, C. G. (2010). Mayo clinical text analysis and knowledge extraction system (ctakes): architecture, component evaluation and applications. *Journal of the American Medical Informatics Association*, 17(5):507–513.

Scheuermann, R. H., Ceusters, W., and Smith, B. (2009). Toward an ontological treatment of disease and diagnosis. *Summit on translational bioinformatics*, 2009:116.

Smelcer, J. B., Miller-Jacobs, H., and Kantrovich, L. (2009). Usability of electronic medical records. *Journal of usability studies*, 4(2):70–84.

Stanford Medicine, T. H. P. (2018). How doctors feel about electronic health records.

The Secured Health Information Network Exchange (2019). About shineos+.

Tsoromokos, D., Tsaloukidis, N., Zarakovitis, D., and Lazakidou, A. (2017). Use of the dpp4bit system for the management of hospital medical equipment. In *ICIMTH*, pages 161–164.

Washington, N. L., Haendel, M. A., Mungall, C. J., Ashburner, M., Westerfield, M., and Lewis, S. E. (2009). Linking human diseases to animal models using ontology-based phenotype annotation. *PLoS biology*, 7(11):e1000247.

Zaman, S., Sarntivijai, S., and Abernethy, D. R. (2017). Use of biomedical ontologies for integration of biological knowledge for learning and prediction of adverse drug reactions. *Gene regulation and systems biology*, 11:1177625017696075.