Modern Extensions to Hospital Information Systems

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ABSTRACT
The aim of this paper is to inform both healthcare practitioners and software solutions creators about the ways in which the Hospital Information Systems (HIS) can and should be extended, both in terms of managing, processing and learning from the data, keeping in mind the sustainable modern technologies available for automation and machine learning. The paper provides details on how ensembles can be implemented and integrated into HIS and also provide the details for the necessary hardware and integrating that hardware to facilitate automation. The paper's target audience is primarily developing countries where these systems, which are yet to become sophisticated, could have a huge social impact.

General Terms
Hospital Information Systems, Healthcare Informatics, Machine Learning, Ensemble Learning, Automation.

Keywords
Hospital Information Systems, Healthcare Informatics, Electronic Health Records, Machine Learning, Ensemble Learning, Neural Network, Automation, RFID, NFC, Android.

1. INTRODUCTION
Today, the amount of the healthcare-related data has increased exponentially in comparison to past 100 years. This unprecedented growth is natural with increase in number of sources of data like sensor data acquired from medical instrument and monitors [1] and falling cost of storing data on a computer media [2]. Health Informatics functionally depends on the field of computing, specifically Software Engineering, Data Science and Machine Learning.

Hospital Information Systems (HIS) aim for centralize and thus provide a patient's health history. Centralization allows to share data among the (medical) community and aid in research and even commonplace like diagnosis, provides necessary reports to the government as well as non-government organizations, provides easier and more efficient manner to perform audits (governments and insurance companies, for example). The focus is more at hospital's record then the patient's.

With advent of smartphones computing power is as good as being ubiquitous. These smartphones can be used for plethora of reasons and purposes: providing remote diagnosis, improving portability of medical records like medical and diagnostic history and test results, reducing menial work, reducing number of errors, providing drug information, increasing drug and disease awareness, etc. Further, a research proves that use of a computer in exam room allows higher satisfaction for researchers as well as patients [3].

These factors allow us to envision the importance of Electronic Health Records (EHR) for the progress of healthcare informatics. EHRs are patient-centred digital records that facilitate real-time secure access of patient records. These have several added advantages over the paper-based records as these focus on the total health of the patient rather than just the clinical data. For a detailed comparison, refer [4]. The data from these EHRs can be processed to enable healthcare providers to make better decisions.

For a cohesive implementation of Hospital Information Systems, it is vital to have an e-prescription system that is shared by all healthcare facilities. The degree of interoperability of e-prescriptions served by different healthcare facilities is one deciding factor for the successful implementations of any such system. These e-prescription systems offer a far greater wealth of data not only to healthcare practitioners but also to patients and various governing agencies.

Besides, this intersection of health-care, computing and information technology affects professions of health information manager and health information technician (aka clinical coder).

This paper explores how the current implementations of HIS that target mostly scheduling of patients be extended. The paper involves discussion regarding the implementation of learning algorithms and how they can be integrated in HIS. The paper further covers how RFID based technologies can be used to improve data capture and automation. The paper targets developing countries that still rely on pen and paper based systems in this industry to allow system developers in such countries to build systems that utilize their true potential and are not simply a scheduler or data entry portal.

2. LEARNING IN HEALTHCARE INFORMATICS
The advancements in the allied fields of artificial intelligence are evidently beneficial to healthcare informatics. Traditionally, data from EHR was utilized more for billing purposes rather than for data analytics. With computational issues out of the way, machine learning has started to provide tools to assist healthcare practitioners and build intuitive predictive models for preventive healthcare. This is done by computing different concepts describing the patients from EHR, known as phenotypes. Learning algorithms are able to sift through vast amounts of data with the goal of finding combinations that predict outcomes. Such combinations are commonly inferred by classifying clinical data into classes; or regressing data to predict behaviour of random variables.

Concepts computed from EHR are called as phenotypes. Phenotyping algorithms can be based on rules established by healthcare practitioners based on evidence from past patient outcomes or can be derived using various learning algorithms. On computation of these phenotypes, patients with the same phenotypes can be grouped together and make decisions based on these phenotypes. [5]

Research on heart disease prediction using Naïve Bayes, k-NN, Decision Trees [6], on cardiovascular diseases using RIPPER, ANN, Decision Trees and SVM [7], on breast cancer using artificial neural networks, decision tree and logistic regression [8], on dyslexia using SVM [9] are few among many. Research papers concerning legal, ethical and privacy issues have also been written. [10] [11]

Cancer research is one of the most prominent medical research areas. Several classification algorithms have been successfully applied to classify various types of cancers. Neural Networks and Support Vector Machines are learning algorithms that have been quite frequently used for classification problems in healthcare research. [12] [13] [14]

Inspired by biological nervous systems, Artificial Neural Networks are computational models used to derive meaning from imprecise data that are complex enough to be processed by humans. These adaptive learning statistical devices use several different techniques/algorithms to process patterns in data towards an outcome. ANNs have been widely used to successfully deal with classification problems. [13]

2.1 Tools for modelling Artificial Neural Networks

There are plenty of languages and tools available to model these artificial neural networks. These include, but are not limited to: MATLAB [15], NeuroGraph [16] and most object-oriented languages which provide enough functionality to model these networks with the desired precision. Although selection of the tools, language and environment does affect the result but is miniscule enough to ignore if one is not looking for extreme precision.

Tools like MATLAB allow an easy vectorised implementation of matrix based operations. This along with the ability to plot data to better understand or discover relations between parameters and their influence on the final result makes MATLAB one of those tools that can be used for a quick prototyping of ANNs.

2.2 Implementing Artificial Neural Networks

The network configuration of any ANN is highly dependent on the data it is to be modelled after. The performance of the network is highly contingent on the relevance of the parameters being used for training. Generally, a single hidden layer is sufficient enough to model most problems but the right configuration is found only by trial and error.

For demonstrating the implementation and usage of Neural Networks, Java was used to build a backpropagating neural network. The choice of language is as always dependent on the preferences of the developer and the ease of integration with the HIS. The process followed is as given below:

1. Normalize and clean the data. The data to be used is first normalized so that instances for each parameter vary within a fixed range.
2. Initialize the Network weights in a random fashion. All initial weights were in the range of -1 to +1
3. Partition the entire data set into training set and testing data set. A general practice is to divide the data into 3 parts training set and 1 part testing set.
4. Calculate error for each training instance by feeding the data forward in the network. For training, mean square error or cross entropy error is preferred over classification error. (A good explanation for the same can be found here [17])
5. Backpropagating the error over the entire network as per each node's contribution to the overall error (i.e. using partial derivatives) and adjusting the weight matrix.
6. After a decent number of training epochs, use the test set to determine the performance of the network/classification accuracy of the network.

While updating the weights, it is essential to regularize the updates so that a single outlier does not hamper the performance of the network. A network that is generalized in order to achieve an accurate prediction for instances other than the ones in training set is the desirable goal. There are several regularization techniques available such as L2 regularization, L1 regularization, Max norm constraint and Dropout [18]. The authors used Max norm constraints to clamp weight updates to a constant value in order to prevent exploding updates.

Furthermore, the authors chose the sigmoid function as the activation function for each neuron. The algorithm requires computing sigmoid values constantly and can hamper performance. To improve the performance, interpolate a fixed number of values of the sigmoid function and use the closest value in the neighbourhood of pre-computed value as the output. This should decrease the processing time needed for each neuron in the network.

The data used henceforth is publicly available in UCI Machine Learning Repository [19]

The first data set tested was the Wisconsin Breast Cancer Data Set. The results were excellent, with the network achieving a classification accuracy of 99.43%.

2.3 Building the ensemble

For more complex and skewed datasets, along with balancing the class distribution of the samples and/or bootstrapping, authors adopted the following methodology:

1. Perform a grid search over a wide variety of hyperparameter values. (Learning rate, Momentum, number of layers and number of neurons in the hidden layers.)
2. Select the best performing networks. (The 8 best network configurations were chosen based on their classification accuracy over unseen samples)
3. Use forward search i.e. starting from the best performing network, to find the best performing combination of networks. This is done by trying out each network combination with new networks added using forward search.

The above methodology can be used for combining with other classification algorithms such as SVMs, Random Forests, etc. as well. Ensemble methods [20] are used to combine various learners to improve accuracy and generalization as compared to a single classifier.

The authors used the Java Serializable interface to store the state of each network into a byte stream. This was done to utilize these networks to predict live data as and when they are entered in the system.

2.4 Results

The tables below show the results the authors achieved after selecting the best performing networks based on the methodology and implementation described in the previous sections:

Table 1. Networks for Indian Liver Patient Disease dataset

Sr. No.	No. of neurons in hidden layer	Training/ Learning Rate	Momentum	Classification Accuracy (%)
1	5	0.2	0.05	78.0822
2	5	0.1	0.1	77.3973
3	5	0.05	0.15	77.3973
4	7	0.25	0.0	77.2973
5	7	0.05	0.15	77.2973
6	11	0.1	0.15	77.2973
7	5	0.2	0.0	76.7123
8	5	0.25	0.0	76.7123

Table 2. Networks for Liver Disorders dataset

Sr. No.	No. of neurons in hidden layer	Training/ Learning Rate	Momentum	Classification Accuracy (%)
1	12	0.1	0.15	79.07
2	6	0.1	0.0	77.907
3	12	0.3	0.0	77.907
4	5	0.25	0.1	76.744
5	5	0.35	0.1	76.744
6	7	0.15	0.0	76.744
7	11	0.3	0.05	76.744
8	12	0.25	0.05	76.744

Table 3. Networks for Diabetic Retinopathy Debrecen dataset

Sr. No.	No. of neurons in hidden layer	Training/ Learning Rate	Momentum	Classification Accuracy (%)
1	14	0.05	0.15	80.488
2	24	0.05	0.05	80.488
3	10	0.05	0.05	79.791
4	20	0.05	0.1	79.791
5	16	0.05	0.1	79.0941
6	10	0.05	0.1	78.746
7	18	0.05	0.0	78.397
8	14	0.05	0.15	78.397

The ensembles were then computed based on the methodology stated in the previous section. Preliminary testing shows the implementation methodology used in this paper, on an average, achieves an accuracy better or on par with other classifiers tested. The WEKA [21] tool was used for comparison. The overall classification accuracy achieved for all the data sets including performance measures of sensitivity (true positive rate) and specificity (true negative rate) for the ensembles tested are shown in Table 4 and Table 5 respectively.

Table 4. Result Summary

Sr. No.	Datasets	No. of Attributes	No. of Instances	Accuracy (%)
1	Breast Cancer Wisconsin	10	699	99.43
2	Indian Liver Patient Disorder	10	583	82.192
3	Liver Disorders Dataset	7	345	83.721
4	Diabetic Retinopathy Debrecen	20	1151	83.624

Table 5. Additional Performance Measures for Ensembles

Sr. No.	Data Sets	Sensitivity	Specificity
1	Indian Liver Patient Disorder	0.7895	0.8333
2	Liver Disorders	0.9286	0.8333
3	Diabetic Retinopathy Debrecen	0.8591	0.8116

2.5 Integrating with the HIS

The prediction made by the ensemble is not recommended to be used as a driving factor in making decisions in a clinical environment. The goal is to bring to attention of the doctors, those patients that the ensemble predicts to have the disease in question, based on the test result predictions, much faster to ensure a faster diagnosis or confirmation by an actual expert. These techniques are not meant to replace an expert but are targeted towards reducing the efforts required by him to sift through every test result.

The ensembles were also tested to simulate real world performance wherein the system is constantly being fed new data. The ensemble replaces the classifier that most affects the classification accuracy with a different configuration using the above methodology, but for that single classifier. Similar if not better results than the above results shown were achieved.

Furthermore, for any learning algorithm to work well in this space, requires an expert to classify the importance of each feature of the data set. This is essential to further improve the accuracy of the algorithm.

3. AUTOMATION

Automatic Identification and Data Capture (AIDC) are a set of methods or technologies that can identify objects by collecting some data about them and provides ability to enter the data into a computer system. Consider barcodes the most widely known technologies of these. Pattern on barcodes (which basically represent numbers) identify them. Barcode scanners scan the pattern (decode them to the numbers) and feed them in a computer system. Thus, applying a barcode (having unique number/pattern) on an object allows to identify them.

A typical hospital today stores large amount of resources (medical/electronic equipment, general purpose computers and records for administration and even objects owned by patients admitted) that do not belong to anyone in specific. Many of these objects are sanctioned by the hospital management, used by doctors and nurses and maintained and stored by nurse or by a different another staff. These devices, that play a critical role in a patient's health [22] [23] and hospital's business, are large in quantity. This makes Supply Chain Management and Inventory Management crucial. Task of identifying all patients, maintaining their records, their current conditions is in itself an enormous task. Immense amount of manual effort (most of which gets classified to being called as "menial") play a large role for amount of death caused. Technologies that are part of AIDC can play pivotal role in introducing automation, tracking, and in improving overall management. Next section covers RFID technology along with its applications. However, these applications can also be achieved, with variation in effort and convenience, through other technologies under AIDC.

3.1 RFID

RFID (Radio Frequency Identification) is a technology, vaguely putting, like barcodes. Instead of a barcode label it uses a tag. “Identification” takes place by a reader which reads the content of memory on the tag. RFID tags have two parts: an Integrated Circuit for handling data, modulation/demodulation and other function while the second part is antenna which is used for reception and transmission of signals. The memory used on tags is non-volatile that is memory content is retained even when tags are disconnected to power source. The “reading” takes place through the use of electromagnetic field. This allows RFID systems to operate without having the reader and the tag to be in the line of sight. Also, since electromagnetic field can penetrate solid objects, an RFID tag can also be embedded or hidden.

There are many factors to consider while purchasing. Tags and readers themselves are of 2 types: active and passive. When active, the component (tag or reader) initiates the communication with the other component. This implies requirement of a power source (generally battery) to run the circuitry and generate radio waves. Passive components respond to active components and do not require a power source. Power required to generate radio waves is induced from incident radio waves. Thus, RFID systems must have at least one active component which generally is the reader while tags are passive. Active readers are capable of both reading a passive as well as active tags while passive reader can read only active tags.

Tags, specifically, have a third category called semi-passive or battery-assisted passive. These tags have a battery but only to run its own circuitry. For communication, it acts like a passive tag - drawing power from incident radio waves. Based on the type of readers and tags, RFID systems are classified as ARPT (Active Reader Passive Tag), PRAT (Passive Reader Active Tag) or ARAT (Active Reader Active Tag).

There are some more factors to be considered before choosing an RFID tag. Tag memory may be read-only or read/write and may or may not have factory assigned serial number. Tags have a variable range; this range can be improved using an antenna. Other important factors are form factor, memory size, tag size and weight, operating frequency, operating temperature, protocols supported, shelf life, maximum number of read/writes, supported cryptographic standards, compatibility, etc.

These factors have a direct impact on cost of the system, efficiency of its implementation and the scope of the application of the system. For example, active tags can be read even in the range of 100 meter. Such tags are particularly useful for applications like locating, tracking and monitoring. While passive tags which have smaller range can suffice for applications like access control, identification and data capturing. Form factor can also play a major role on cost. Generally, labels are much cheaper than hard tags. This also implies an effect on range as well as size and weight.

Memory provided by tag manufacturer have a set of bits reserved for EPC (Electronic Product Code) and user. EPC provides a syntax for uniquely identifying objects, location and other identifiable entity. These unique numbers assigned to each tag can act as a patient’s or equipment’s identification number [24] and can act as a key in database systems. This leads to seamlessness. With some effort on integration, it can also be used for maintaining their reports, past prescriptions and other elements of medical history, further increasing the seamlessness of the system. This would enable the healthcare institutions to automate the processes like registration, billing, payment, tracking of dispensaries, management of staff and patients, etc. [25]

Besides automating the general workflow, these tags can be used to enable access control, asset tracking, locating, tracking and monitoring patients and protecting drug supply chain from being counterfeited or thieved [24] [26] [27] [28] [29]. Asset tracking allow tracking, controlling and better management of inventory, equipment, drugs and even laundry.

As a downfall, these RFID systems raises many security and privacy concerns [30] [31]. To counter the security issues, standards have been developed which take measures like on-chip cryptography and digital certificates to allow untraceability, authentication and protection of privacy.

3.2 NFC

Every smartphone today carries a RFID-like technology called NFC (Near Field Communication). For healthcare institutions like hospitals in rural or remote areas, clinics or any small-scale institution can adopt NFC on the smartphones instead of conventional RFID tags. It works on similar lines and is much more cost-effective. In fact, NFCs can help an institution to deal with outpatients and tags can accommodate inpatients.

Android Operating System provides good support to interact through NFC. This applies for both – NFCs embedded in other Android devices as well as NFC tags and stickers. This communication usually can take place in three modes to suit the various requirements. First mode is Reader/Writer mode where the Android device reads/writes NFC tags/stickers. This mode suits when generally short-ranged RFIDs suits well. Second mode is P2P for communication between two Android devices themselves. This allows an alternate way for exchange of data between Android devices (including multimedia). The last mode is Host-based Emulation which lets Android devices behaves like an NFC devices. It lets Android devices act as smartcard whatever maybe the scenario.

Not all Android devices have NFC chip, but most high-end devices do have it. Such cases can be covered with alternative technologies like Bluetooth or Wi-Fi. These technologies can be more suitable and convenient in many cases but at the cost of seamlessness; communication through NFC does not require discovering or pairing.

3.3 Integrating with HIS

Three use cases were covered while testing an implementation during the writing of this research paper. First was to use an Android application for outpatients. This allows them to be part of the system as they appear and the application also helps patients manage their own profile and records. Second use case is for inpatients, where email id was stored over the NFC tag which could be retrieved by a reader or an Android phone (of doctor's). Third use case was doctor's application which could communicate with both patient's Android application as well as NFC tags and could prescribe using the same application.

RFIDs have already proven its efficiency and efficacy to many healthcare institutions for applications like asset management and patient tracking [32] [33] and to create a porter management system [34]. Top-notch organizations outside healthcare like Wal-Mart and USA's DoD have also been using RFID for many applications. Following is a table that lists few RFID tags with few factors.

Table 6: RFID tags from well-known manufacturers

Model Name	Range	Memory in bits			Form Factor
		EPC	User	TID	
Xerafy Titanium Metal Skin	1.2 m	128	32	48	Label
Xerafy Dash-On XS	2 m	96	512	64	Hard
Omni-ID Fit 200	2.5 m	96	512	64	Hard
Omni-ID Fit 210	3 m	96	512	64	Hard
Confidex Steelwave Micro	3.5 m	128	512	48	Hard
Alien ALN 9740 Squiggle	4.57 m	128	128	32	Wet Inlay
Xerafy Mercury Metal Skin	5 m	496	128	48	Label
Confidex Steelwave Micro II	5 m	128	512	48	Hard
Xerafy Nano X II	6 m	96	512	64	Hard
Confidex Halo	8 m	240	512	64	Hard

4. OTHER SOFTWARE SOLUTIONS

Many healthcare-related software have become commercially available for different purposes like electronic health record maintenance, practice management, patient scheduling, office management, information systems, data management, and for research and data mining in a particular field. Among these few are web-based which removes any hassles for the healthcare institution of installing software. The progress has gone much beyond developing standalone software solutions, protocol (HL7), standards (openEHR, DICOM) and committee and consortium (ISO/TC 215, CDISC) too have come into existence.

Among the software solutions, GNU Health is the most noticeable hospital information system. It is *free*, cross-platform, scalable enough to be useful from private offices to national public health system, has highly modular design and can acts as all three – Hospital Information System, Electronic Health Record, and Health Information System. Since the source code is available to all, it can be modified and distributed (both original as well as modified code) by any individual or institution as they wish to. Other software like Mirth and OpenEMR are not only open source and scalable to real scenarios but also provide professional support for a healthcare institution.

5. DISCUSSION

Before building a system that can have wide implications and huge impact on the society, it is important to understand the attitude of the general populous towards such a system. To understand the public opinion and sentiment regarding the prevalent system, the authors conducted a survey of 50 people aged between 18 and 23. The survey was conducted in Mumbai, a city in India. The survey revealed how dissatisfied the people are with the current pen and paper system prevalent in India.

The Figure 1 shows the results for the percentage of people who seek a more explanatory prescription. A staggering 70% wanted their prescription to provide more data.

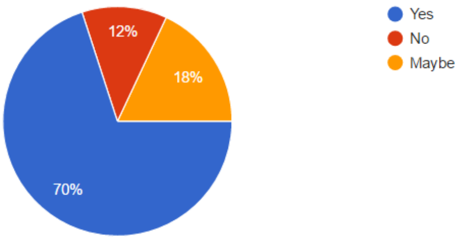

Figure 1: Survey Results 1

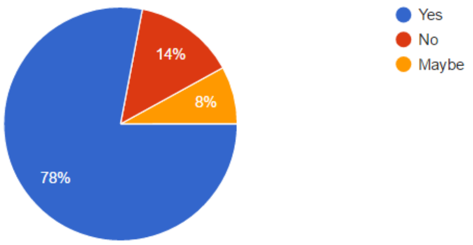

Figure 2: Survey Results 2

Furthermore, 78% of respondents (Refer Figure 2) wanted their prescription to specifically address side effects of the drugs prescribed and 74% of the respondents think that a switch to digital medical records will help them in attaining the requisite medical care (Refer Figure 3).

These results show the growing urge amongst the general populous for seeking a more transparent and informative system. Given how accepting the society has become towards information systems effectively replacing traditional procedures in various fields, HIS should have a high acceptability rate amongst the populous.

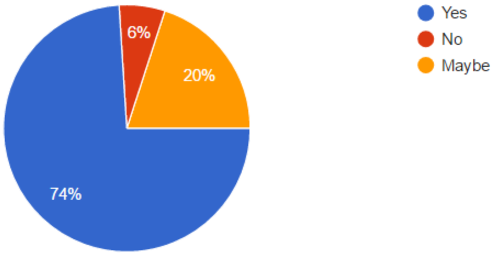

Figure 3: Survey Results 3

These systems can only be effective in bringing about a radical change if health institutes of all sizes operate on the same platform. Interoperability of data between healthcare institutions is a necessary factor for such systems to succeed. This interoperability should not be limited to a country as well. Such coherent system will not only improve the process of attaining medical care but also improve data availability for researchers.

6. CONCLUSION

With an exponentially growing population in most developing countries, an effective HIS can drastically speed up the process of attaining requisite healthcare and also improve the quality of care being provided. The technical and implementational details for modern extensions to HIS such as machine learning and automation techniques have been provided and should facilitate their integration with traditional HIS. Machine Learning will help conceive a clearer and sharper idea for better treatment and management of patients and even lead to prevention of a disease from becoming an epidemic. Automation, on the other hand, will help in smoothening this process (of data collection) and increase its efficiency and accuracy and would help authorities in better accounting and auditing of resources. These systems ideally should provide complete solutions to healthcare institutions of all sizes.

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