Learning Algorithms in mHealth Applications

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CONTENTS

***Abstract*—Mobile health is positioned to aid the health care system by offering the feedback of a physician without consultation. The purpose of this paper is to analyze artificial neural networks (ANNs) as a viable option in mobile health applications to create automated medical diagnostics. To determine the likelihood of such algorithms, ANNs were reviewed to see how they fair as classification models for replicating clinical diagnostics. It was found that several ANN's already existed for such diagnostics and performed well enough to be of aid to physicians. Based on these accurate performances, research on ANN's, driven by the popularity of smartphone health applications, could produce automatic medical diagnostics for patients outside the clinic.**

1 Introduction

Over the last decade, mobile health (mHealth) has been an expanding field of electronic health (eHealth). eHealth is an umbrella term encompassing any health care practices aided by electronic processes or communication, while mHealth revolves around the same practices but is fixed on mobile phones and other wireless technology. The field has left an impact on the health sector, producing remote monitoring technologies such as mobile trackers for cardiac activity, glucose levels, exercise, calorie intake, and sleep cycles. Though still in its infancy, mHealth is poised to become an asset to health care, physician and patient side alike. The field proposes new ways to engage health care, allowing patients to take a more extensive and personalized approach to their own care through wearable and mobile devices.

2 Background

2.1 Before mHealth

Given mHealth's nature of focusing on out-of-hospital care, any sort of remote monitoring tools such as a remote cardiogram were non-existent prior to mHealth. Instead, telehealth was the primary predecessor, which concentrated on sending data between hospitals rather than sending to hospitals directly from patients. Telehealth is an umbrella term encompassing "any means of delivering health care and the exchange of health-care information across distances [7]."

Taking internet and phone lines out of the equation, telehealth can be dated back to the Middle Ages when the first health surveillance system was established for transmitting information about the bubonic plague across

Europe via bonfires. The first instance of modern telehealth, however, occurred in 1906 when Dr. Willem Einthoven, inventor of the EKG, developed a way to transmit his EKG data over telephone lines [8]. This initial act received widespread attention, given the publics foreseen applications of this technology with a 1920's issue of Popular Science magazine foretelling of "radio doctors."

However, these "radio doctors" would never come, at least not in the sense people were imagining. In fact, the next incarnation of modern telehealth occurred over forty years later, brought on via the making of the television, by a hospital in Nebraska establishing a close circuit television connection to a hospital one hundred miles away; allowing for consultations between specialists and general practitioners [7]. These early forms of communication were the closest thing to modern mHealth until progress in remote monitoring was made.

2.2 *Initial Phase*

Remote monitoring devices are where the origins of mHealth lie. Beginning in the field of biomedical engineering, researchers became interested in wireless and sensor technologies which could monitor one's health at a distance [20]. Early examples included cardiac, blood pressure, pulse oximetry, and glucose monitors [1]. Each device featured wireless telecommunication allowing data to be transmitted to health care providers or third parties. While these devices are still in use today, many lacked features preventing them from being true remote monitoring systems, or rather, mobile systems that could follow patients anywhere. Instead these devices were mostly used in settings such as nursing homes and veterans hospitals where medical staff were still nearby to provide assistance. As the devices improved, features were added such as education on use, reminder alerts, and means of communication between the patient and provider: making these devices more user-friendly, but still not something that could be transported comfortably. Drawbacks of these products included bulkiness and limited to only measuring one metric, making it difficult for a patient to carry multiple devices. It was clear these devices were built with the intention of being used in the home setting as opposed to on the go. And while these devices successfully served their purpose in allowing patients better care outside the hospital, it wasn't until the smart-phone that mHealth became what it is today.

2.3 *Catalysts*

The early 1990's are where the first mobile phones appeared on the market and have since been in a consistent state of evolution [9]. These devices have expanded their memory and processing capabilities, included geospatial tracking, hosted touch-screen technology and accelerometers to track movement [14]. Some even contained remote monitoring devices with embedded cellular modems to transmit data independent of the smart-phone's signal. With all these improvements, smart-phones now possessed the ability to monitor an entire series of behaviors [9].

And with advancements in hardware technology lowering costs of connection and data plans, the smart-phone significantly penetrated society, appealing to the entire age spectrum of its subscribers, from school children to senior citizens [5]. In the United States alone, there are an estimated 164 million smart-phone users, with projections into 2018 estimated to hit 220 million (Fig. 1) [27].

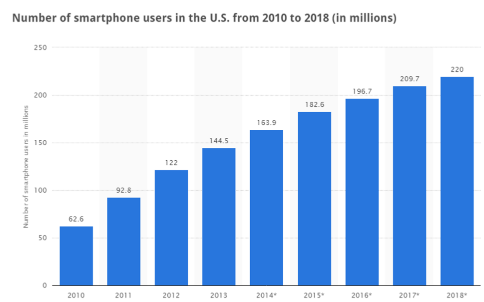

Fig. 1. The number of smartphone users in the United States was over 160 million in 2014, with projects reaching 220 million by the year 2018. [27].

Looking to global statistics (Fig. 2), the year 2014 hosted over 2.5 billion smartphone subscriptions, with projections into 2019 estimating over 5.5 billion subscriptions, more than doubling the number of subscriptions in the next 5 years.

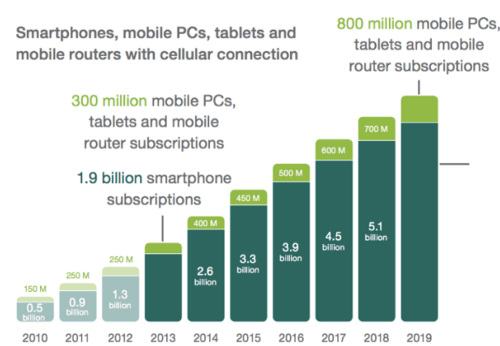

Fig. 2. The number of smartphone users globally was over 2.5 billion in 2014, with projects reaching 5.5 billion by the year 2019. [22].

Smart-phone popularity, however, isn't the only catalyst for mHealth technologies.

Consumer demand has also played a driving role in mHealth applications. In 2010 there was an estimated revenue of $104 million, with estimates only two years later jumping to $1.3 billion, averaging a tenfold increase [21]. In 2013 there were an estimated 97,000 mHealth applications available in app stores [25]. And estimated revenue from these apps is expected to hit $23 billion by 2017 [21]. While this provides good incentive for developers to keep an interest in the mHealth market, consumers also benefit. These apps have enhanced many aspects of consumer engagement in health care such as "increasing the flow of information; lowering costs through better decision-making, fewer in-person visits, and greater adherence to treatment plans; and improving satisfaction with the service experience [14]." And while these benefits are being seen in technologically advanced countries, developing countries are where these applications are having the greatest impact.

2.4 *A Pressing Need*

This new found access to mobile communication infrastructures in developing countries has allowed people in these areas access to communication and information channels, via simple handsets, which were previously unavailable [20]. Perhaps the final catalyst for mHealth development came from work done in these countries out of necessity for basic access to health care. People could now contact physicians and medical staff to ask questions and call for emergency transportation or medical services.

Other advancements such as SMS frameworks (SMS standing for "short message service," also known as the texting component of phones) provided support tools allowing health workers to manage their client base more effectively [20]. These services also allowed for many health advancements such as early infant diagnosis for HIV, prevention of diseases from mother to child, birth registrations, diagnostic support, and clinic based structured reporting: where clinics track patient cases and keep inventory of medical supplies. Finally, data collection on PDA's regarding various health issues such as immunizations and health demographics also benefited these countries.

There is a significant shortage of medical staff in these countries, but mHealth technologies are beginning to ease the burden. In Africa, for instance, there is an estimated shortage of 800,000 workers and to make matters worse, it's difficult to recruit and retain these health care workers due to such poor working conditions [18]. In addition patient supervisory and management systems are often weak or non-existent as well.

Fortunately mHealth technologies are helping to remove physical barriers to service delivery and strengthening health systems/patient management, unreliable supply systems, and poor communication. While never intended to be a driving force for mHealth technology, this untapped pressing need for better health care services in developing countries has quickly spurred an immediate series of advancements, easing the burden on the people in these countries and allowing them access to higher quality care.

2.5 *mHealth Today*

In fact, access to higher quality health care is becoming the standard to anyone with a smart-phone; with mHealth apps becoming commonplace on the mobile market. A study taken from 2013 surveyed the amount of mHealth related studies conducted the past decade. Looking at the field in review, the trend was discovered that initial research projects focused on evaluations of the mobile technology itself and slowly moved towards assessments of impact on health outcomes [9]. In these later studies it was observed that an increase in positive interventions was made with an overall positive impact over time. Given these observations, it was concluded that the field is becoming more structured and coherent.

Taking into consideration the large number of people carrying smart-phones, paired with the number of health related applications being downloaded, mHealth has become an integral part of modern health in the past few years. For example, medical students in Georgetown are now required to have an iPhone, as surgeons are noting the platforms usefulness in improving diagnostic skills and education via its apps. Insurance companies are promoting mobile technologies from sharing information about hospitals and physician performance to encouraging self-care for patients with chronic conditions not requiring intense physician care. And pharmacists and drug stores are using mHealth to bring information to consumers, offering therapeutic solutions complementing traditional treatments, often saving consumers time and money.

Fortunately there is the eagerness of those outside the health care industry to utilize everything being offered, be it accessing information, participating in self-care via monitoring services, or keeping in touch with their health care providers [5]. With new sensors, apps, and other programs being developed that target chronic conditions, remote monitoring, patient data capture, electronic records, e-prescribing, and fitness and wellness, it seems the health care environment is moving towards a patient-centered care model consisting of individuals being active participants in managing in their health care, allowing medical staff opportunities to create higher quality and highly personalized health care plans [14].

3 Technical Aspects of Artificial Neural Networks

Only with modern technology has achieving the goals of mHealth become more feasible. With significant percentages of the global population now owning a device that can harness the applications mHealth has to offer, the way health care has been conducted is changing. Control is shifting to the patients giving them the ability to track their own biometrics and access countless sources via the internet. But what if something more could be done? Instead of biometrics being monitored by physicians who would then analyze the data and inform the patient of any potential issues, what if the analysis could also be done right in one's pocket? What if a program could take those metrics and make something of them as soon as they emit a pattern? To accomplish this, it would seem the next logical step for mHealth is integration with artificial intelligence and machine learning programs, offering opportunities to warn patients of potential risks as soon as possible. Such a system could be implemented through an artificial diagnostics program. The program could take in the user's various metrics and check them across a database of illnesses looking for a potential match.

3.1 Components of Artificial Neural Networks

Networks are a prime candidate for such a system. While various types of networks exists, they all share two common features: a set of nodes, and connections between the nodes [12].

3.1.1 Structure: Nodes can be considered computational units: each node will receive an input, process that input, and then produce an appropriate output [12]. For example, a node's behavior may be as simple as receiving a number, adding a value of one to it, and then exporting the sum. The connections between these nodes determine how information should flow throughout the network; moving in a unidirectional or bidirectional manner: information can be passed to forthcoming nodes only, or based on behaviors in the later nodes, information may be passed backwards as well. While the behaviors of the individual nodes may not amount to much, the interactions between these nodes lead to an overall behavior of the network. In other words, the whole becomes greater than the sum of its parts.

Of these networks, the most common type seen for purposes of medical diagnostics is the Artificial Neural Network (ANN). The ANN is based on the behavior of neurons. Referring to Fig.3, the neuron receives signals through the dendrites and then if the signal received is strong enough to pass through the threshold, the neuron activates and sends the signal out the axon. This signal is then sent to other neurons or synapses in the brain.

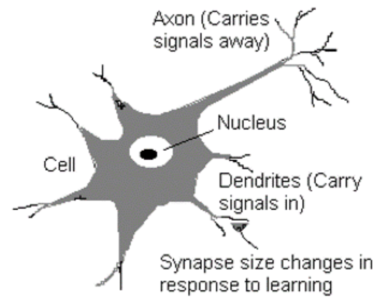

Fig. 3. The electrical signals are carried by dendrites into the neuron which then decides if the signal is strong enough to be carried out by the axon to other neurons, or left in the cell [12].

Though not entirely similar, these structures act as a model for artificial neurons. Looking at Fig.4, a similar setup can be seen. These artificial neurons are made up of inputs which are multiplied by weights and taken into mathematical functions which determine whether the artificial neuron will posses a strong enough value (or signal) to activate (or pass through the threshold). If activation is accomplished, the value may be sent to another node for further computations, or the information will be passed along to an output node. In more complex ANNs such as Fig.5 the inputs may pass through hidden layers which are layers in addition to the input and output layers and typically host extra computations [26].

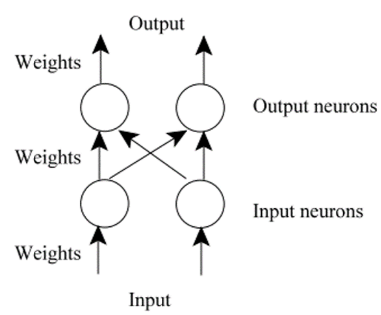

Fig. 4. The anatomy of a simple ANN: Inputs are carried into the network by input neurons which are then manipulated by weights and carried to output neurons which decide if the values are high enough (or strong enough) to be outputted by the network [26].

3.1.2 Weights: Weights primarily determine how strong the inputs will be, the higher the weight, the more strength the input will be given (the input is multiplied by the weight). To better explain this, referring back to Fig.4, two inputs are taken in and multiplied by different weights, looking only at the first half of this diagram, say the weight on the left has a value of 2, while the weight on the right has a value of 5. If both incoming inputs have a value of 1, then the weight on the right will produce a higher value (or stronger signal) than the weight on the left, making the right node (at least for this first part of the diagram) the prime candidate to be outputted.

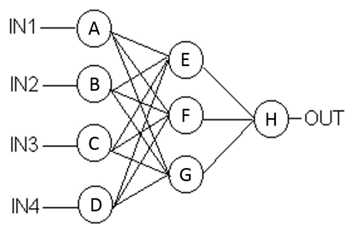

Fig. 5. Another example of the anatomy of an ANN, the column of nodes "A,B,C,D" represent the input layer, "E,F,G" the hidden layer, and "H" the output layer [26].

These weights can also hold negative values as a method of inhibiting the input, typically seen in neurons used in later layers of networks [12] [10]. Assume from Fig.5 a neuron in the latter layer of the network (layer EFG) is taking in two inputs, one of which is already coming in with the assumption that it is an unlikely candidate, it could be multiplied by a negative weight to ensure that even if the other input doesn't have a high value it will still be considered over the unlikely input.

By setting these weights to various values the correct output can be obtained from select inputs, however, in more complex networks ranging upwards of thousands of neurons, calculating the necessary weights would prove exhaustive.

3.1.3 Biases: Similar to weights, biases also directly affect the inputs of a network. A bias will always initially hold a value of one but can also be weighted [24]. The bias is primarily used in the case of an input value ever equaling zero.

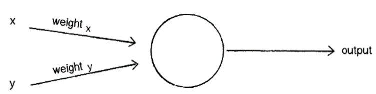

Fig. 6. A simple ANN without a bias [24].

For example, consider a graph of dots with a line through them, a network takes in a pair of coordinates (x and y) and outputs whether the points lie above or below this line. Now what if the coordinates taken in are (0, 0)? If Fig.6, for example, takes in the two inputs x = 0 and y = 0 and then multiplies them by weights, regardless of what the weights are the sum of the weighted inputs will always be zero and therefore the output will always be zero preventing the user from knowing whether the coordinates are positive or negative (or above or below the line). A bias can remedy this situation (see Fig.7) when a weight of 1 is added to both the x and y inputs allowing the weights to still have an effect on the inputs and decide whether the coordinates (0, 0) lie above or below the line.

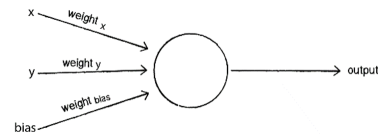

Fig. 7. A simple ANN with the addition of a bias [24].

3.1.4 Learning Algorithms: Algorithms can be developed to adjust the weights to the correct amounts by a process called "learning" or "training." These learning algorithms are modeled after the strengthening and weakening of synaptic connections in the brain. Briefly covering the three main paradigms of learning algorithms, there exist the Supervised, Unsupervised, and Reinforcement Learning algorithms, each possessing unique advantages and disadvantages [17].

- **Supervised Learning -** these algorithms are used when the system is given inputs as well as the correct output during training. The network is able to calculate its margin of error between the correct output and its actual output and then use that margin to make corrections to its network by updating its weights.
- **Unsupervised Learning -** when training the network, only inputs are given and it becomes the algorithms responsibility to find patterns within the inputs provided.
- **Reinforcement Learning -** in this paradigm the algorithm receives its inputs and also a "reward" based on how well the algorithm has performed, the goal is then for the algorithm to try and maximize its "reward" through trial-and-error via setting its weights.

3.1.5 Training Process: Learning algorithms seek to find the optimum configuration of the ANN which is typically accomplished by taking three random samples of the data and producing three independent sets (training, validation, and test) [23]. Referring to Fig.8 may help provide a better understanding of how these algorithms train the network.

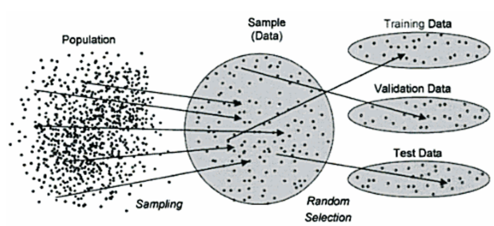

Fig. 8. Sample data is taken from the population and then broken into different sets to be used by the training, validation, and test sets exclusively [23].

- **Training -** The training set is used strictly for what its name implies. It is a set of samples used to properly adjust weights to produce the correct outcome.

- **Validation -** The validation set monitors the error on the training set. This is done by verifying that any increase in accuracy over the training data will also yield an increase in accuracy on data that the training set is unfamiliar with. This is done to avoid **overfitting**, a flaw in which the training set simply memorizes test data instead of rules which govern how the test data should be handled. If the training sets accuracy increases while the validation sets accuracy stagnates or decreases, this is a sign that the network has become overfit. This cycle of moving between the training and validation sets will comes to a halt when the validation set has found an acceptable margin of error.
- **Test -** The test set is for testing data which is completely independent of the training and validation sets. It takes in weights from the training set which have yielded the lowest margin of error and uses them only on new data to test the actual predictive power of the network.

3.2 *Implementation of Artificial Neural Networks*

Having covered the basics of ANNs, there are several types of ANNs and accompanying learning algorithms already being developed for medical diagnostics. These programs range from identifying patients with heart disease to detecting early signs of lung cancer. If proven to succeed in their proposed operations, these algorithms could become an integral part of mHealth's future of keeping patients outside the clinic just as informed as those inside.

3.2.1 Feed-forward Neural Network: The feed-forward neural network has been commonly seen in medical diagnosis for its strength as a classification model [3]. This study in particular utilizes the model for detection of acute nephritis (inflammation of the kidneys) and heart disease. The Feed-forward design (as its name implies) only moves information forward. This model in particular (refer to Fig.9) features the typical setup of input, hidden, and output layers, with the hidden layer consisting of twenty neurons to be trained. Since the hidden neurons in this system are able to learn the necessary pattern in the training phase, no feedback is required. These nodes use a transfer function to process the data they receive from the inputs and then transfer their processed data to the output neurons for further processing using another transfer function in each node of the output layer. The transfer function, represented as

$$\sigma(\sum_{j=1}^{n} w_j x_j + b_j)$$

is the product of each input and weight with the bias then added in [4].

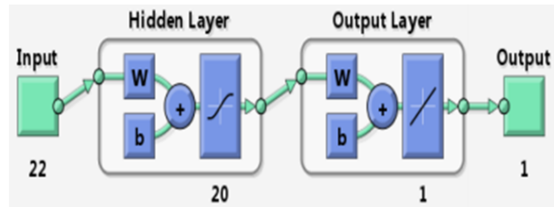

Fig. 9. A feed-forward neural network which diagrams how inputs are computed in the hidden and output layers. These particular computations can otherwise be referred to as transfer functions [4].

3.2.2 Levenberg-Marquard Back Propagation Algorithm: The network utilizes the Levenberg-Marquard back propagation algorithm (falling under the supervised learning paradigm) for the training phase. By feeding examples of the expected outcome to the algorithm it will change the networks weights so that after the training stage it will give the desired output for a particular input [28].

The back propagation algorithm consists of first setting all the weights in the network to random numbers, for example, a range of -1 to +1. The next stage known as the *forward pass* applies the inputs and calculates the output which is unlikely to be close to the target output since the weights are random. However, the error of each node is then calculated from the equation *Target Output — Actual Output*. This error is then used to change the weights in the network so that the margin of error will decrease. Once the margin of error has stopped decreasing this process will cease as the algorithm has reached its minimal error.

The Levenberg-Marquard Back Propagation Algorithm hosts several deviations from the standard back propagation algorithm. One of these is the shift to Newton's method for finding the minimum of a non-linear function, a method which requires finding the functions critical points at which

$$\bigtriangledown f(x) = 0$$

While this method is faster and more accurate, it can only be utilized when error is near minimum [19]. This alteration ensures the performance function will always be reduced upon each iteration of the algorithm.

3.2.3 Results: The data used for detection of acute nephritis consisted of a temperate range between 35 and 42 degrees Celsius (since patients with acute nephritis typically run a temperature close to 40). And five yes or no questions:

- Occurrence of nausea?
- Lumbar pain?
- Urine pushing (Continuous need for urination)?

- Micturition (urination) pains?
- Burning of urethra, itch, swelling of urethra outlet?

The dataset consisted of 120 patients where 90 samples were used in training the network and 30 were used in testing the network.

Results from the simulation classifying patients as healthy and unhealthy based on their symptoms were positive. The simulation was able to classify 99% of the cases in the test correctly, such a high accuracy supports the notion that this model would be useful when detecting patients with acute nephritis.

The same type of neural network was also used for detecting patients with heart disease. This time, however, instead of symptoms, a database of 267 Single Proton Emission Computer Tomography (SPECT) images were used. Patients were classified into "normal" and "abnormal" categories [3]. The database was then processed to find features or patterns which would indicate an abnormal heart. Of the 267 samples, 80 were used in training the network while the other 187 were used in testing the network.

Upon running the simulation it was found that distinguishing between a normal and abnormal heart, based on the binary feature patterns extracted from the SPECT images, showed the network performed well in learning the patterns. For the testing set, the network managed to accurately classify 95% of the cases. The networks accuracy proves that a feed-forward neural network could produce significant results when handling data presented in SPECT images and that the network could be useful for identifying patients with heart disease.

3.2.4 Multilayer Feed-forward Neural Network: ANNs are positioned to be of aid to physicians given their strengths as classification models. And with new software emerging, physicians are now being given the chance to use ANN models in their research without the complexities of designing their own programs to create them [11].

A study done for early detection of lung cancer in patients utilized the Matrix Laboratory (MATLAB) programming language which was described as "exceptionally straightforward." A similar model was used in comparison to the previous study: where data was brought into the input layer, further processed in the hidden layer and output in the final layer. This time the computations done in the hidden layer were based on an accumulation of knowledge from years of studying how an expert uses specific patient data to make the diagnosis. The primary difference found in this model is the hidden layer consisted of only four neurons whereas the previous models contained over twenty.

Again, the back propagation algorithm was used for training the network, further proving that this is one of the most successful training algorithms when the network is focused on classification. However, this particular algorithm did not utilize the Levenberg-Marquard deviations as seen in the previous study.

Upon implementing the model the MATLAB language again received positive marks from the researchers as it "relieved a lot of the mundane tasks associated with solving problems numerically, powerful operations could be performed using just one or two commands, and included high-level functions for two-dimensional and three-dimensional data visualization, image processing, animation, and presentation graphics" as demonstrated by the detail summations in Fig.10.

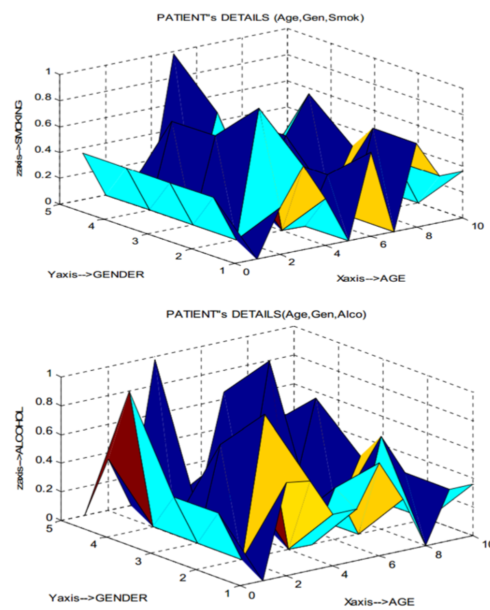

Fig. 10. An example of the MATLAB languages ability to generate three-dimensional graphics based on data provided [11].

The results showed that of the one hundred lung cancer data sets collected, with parameters of age, gender, and frequency for smoking and alcohol consumption, the algorithm gave over 87% accuracy, quite a bit less than the previous study. However, the advantage was that the algorithm would only take a few seconds of execution time and that modifications would be made to raise its accuracy in the future.

Although unlikely to stand on its own, the network in its current state could still prove useful as a source for physicians to confirm their diagnosis, or to use as a starting point when first examining a new patient. And while the accuracy rating did not reach as high a level as the previous study, the fact that such an accuracy rating, especially in early stage diagnosis, could be generated using software not specifically built for early lung cancer detection is still an impressive feat. Emphasizing the eased burden of creating such networks while still maintaining high accuracy, proves ANNs can be efficiently implemented in medical research.

4 Future Trends

This implementation of ANNs into medical research represents one of the factors necessary for mHealth to provide it's most significant contribution to the health care system: automated medical diagnostics. Additional factors such as popularity of smartphone health applications and biometric tracking will lay the groundwork for automated diagnostics in the next three to five years.

4.1 Popularity of Smartphone Health Applications

Having previously covered smartphone statistics (refer to pg. 2), no evidence is necessary to support smartphone popularity.

With smartphones acting as an attractive platform for applications, the mHealth market is no exception. With 97,000 mobile health apps across 62 app stores leading to the top 10 apps generating 4 million free and 300,000 paid downloads each day [6]. These rates are expected to jump to 1.7 billion health apps being downloaded by 2017, projected to generate $23 billion in revenue (Fig. 11) [13].

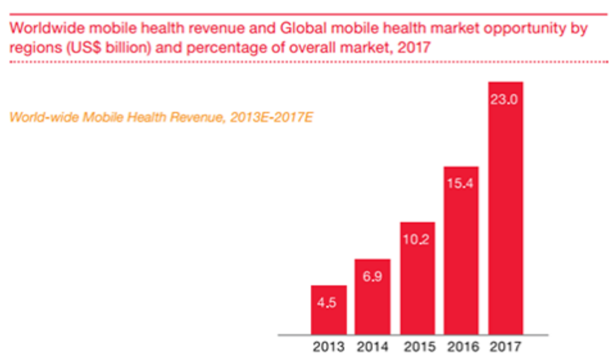

Fig. 11. The mHealth market reached almost seven billions dollars in revenue for the year 2014 with projections estimated to reach twenty-three billion by the year 2017 [13].

Based on these predictions, global interest in mobile health applications will be growing in the next 3 years.

4.2 Tracking Biometrics

Many products are being designed and released which allow for monitoring of a user's various metrics. The first product to note is the upcoming Wello. Developed by Azoi Inc. the Wello is a smartphone case which tracks various metrics including heart rate, blood pressure, blood oxygen level, respiration, heart-rate variability (stress level), temperature, lung functions, and also includes an ECG [15]. The case features sensors on the back and sides which record all of this data when thumbs are placed on the back sensors and index fingers on the side sensors. Though not yet released, Azoi is claiming the case will host medical grade accuracy and the ability to pair up with various smartphone apps to organize the data.

Another metrics tracking device gaining popularity is the Fitbit, while the Fitbit has been out for several years, the developers are refining it to produce more accurate results: measuring number of steps, distance traveled, calories burned, and sleep quality [16]. While the device isn't tracking the more serious metrics such as vital signs, these factors still play an important role in determining the physical state of a user; and metrics such as sleep quality can be useful when determining the cause of a particular ailment.

The last product to mention is the AgaMatrix iBGStar with the ability to monitor glucose levels for diabetes patients [2]. Again, the product may take a bit of a back seat given its limitations in only monitoring one metric. However, the device still serves a strong purpose; giving those with diabetes easier access to their sugar levels especially when on-the-go.

These products are not the only devices capable of these tasks, there exist a myriad of other mobile devices with the ability to monitor the metrics stated above. And based on this wide range of products, it can be proven that the field of tracking biometrics is in good standing.

4.3 Artificial Medical Diagnostics

To review, several studies have already been completed testing the abilities of artificial intelligence, specifically ANN's in the case of medical diagnostics.

The first study featured detection of acute nephritis, achieving 99% accuracy. Proving the program could be useful in detecting patients with acute nephritis.

The same program was also used for detecting patients with heart disease. This time however, the program referenced a database of 267 SPECT images, achieving 95% accuracy. Proving the same model could be useful in detecting patients with heart disease.

Finally, the third study was done for early detection of lung cancer. With results showing the algorithm gave over 87% accuracy. Again, while this accuracy is less than the previous study, the researchers utilized a language which was less optimized for the data as it was not built specifically for early lung cancer detection. Therefore, the ability of this versatile language to still produce a high accuracy rating with ease shows the language could be an attractive and more common tool in future medical studies.

With AI programs already being developed specifically for medical diagnostics, the second component is also on the right track. With solid support and research being conducted in these two areas, it seems inevitable to combine the two fields.

4.4 Overlap

In addition to the strength of these three factors, perhaps the best piece of evidence for automated diagnostics is research being peformed on the subject itself. In New Delhi, Kanav Kahol along with his engineering team have already built a prototype for a device called the Swasthya Slate (translating to Health Tablet) [30]. The modified android tablet features a medical thermometer, water-quality meter, heart-rate monitor, an ECG, and sensors for tracking blood pressure, blood sugar, blood hemoglobin, urine protein and urine glucose. When sent off to medical labs for testing, the tablet received positive feedback, with performance rates as accurate as any other medical equipment used. As of now, Kahol has programmed the device to perform 33 diagnostics tests, among them: HIV, syphilis, pulse oximetry, and troponin.

With the tablet gaining support in New Delhi, its existence alone is perhaps the strongest piece of evidence that mHealth will be offering automated diagnostics in the home setting in next few years.

5 Concluding Statements

For a field still in its infancy, mHealth has made a significant impact in health care. From lighting bonfires to counting calories, mHealth's overarching goal has stayed the same: "bring the examination room closer to the patients" [29]. Studies utilizing ANNs in medical research have proven there is potential for automated diagnostics. And the popularity of smartphones, healthcare applications, and biometric trackers are providing just the incentive needed to encourage further research which will bring these diagnostics algorithms to users and patients, wherever they are.

References

[1] Technologies for remote patient monitoring in older adults. *Center for Technology and Aging*, Dec 2009.
[2] AgaMatrix. ibgstar diabetes manager. 2014.
[3] Qeethara Kadhim Al-Shayea. Artificial neural networks in medical diagnosis. *IJCSI*, Mar 2011.
[4] Wolfram Alpha. Neural networks documentation. *Wolfram Mathematica*, 2014.
[5] Maged Boulos, Steve Wheeler, Carlos Tavares, and Ray Jones. How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from ecaalyx. *BioMedical Engineering OnLine*, Apr 2011.
[6] Jonah Comstock. Report: 1.7b to download health apps by 2017. Mar 2014.
[7] John Craig and Victor Patterson. Introduction to the practice of telemedicine. *J Telemed Telecare*, 2005.
[8] Tom Farris. A brief history of telehealth. *SecureVideo*, Mar 2013.
[9] Maddalen Fiordelli, Nicola Diviani, and Peter Schulz. Mapping mhealth research: A decade of evolution. *J Med Internet Res*, May 2013.
[10] Ivan Galkin. Crash introduction to artificial neural networks. *University MASS Lowell*.
[11] N Ganesan, K Venkatesh, M Rama, and Malathi Palani. Application of neural networks in diagnosing cancer disease using demographic data. *IJCA*, 2010.
[12] Carlos Gershenson. Artificial neural networks for beginners. 2003.
[13] Zahid Ghadialy. Opportunities for reshaping the future of your industry? Nov 2012.
[14] Harry Greenspun and Sheryl Coughlin. mhealth in an mworld how mobile technology is transforming health care. *Deloitte Center for Health Solutions*, 2012.
[15] Azoi Inc. Wello. 2014.
[16] Fitbit Inc. Fitbit. 2014.
[17] Lee Jacobson. Introduction to artificial neural networks part 2 - learning. Mar 2014.
[18] James G. Kahn, Joshua Yang, and James S. Kahn. mobile health needs and opportunities in developing countries. *Health Affairs*, 2010.
[19] Ozgur Kisi and Erdal Uncuoglu. Comparison of three backpropagation training algorithms for two case studies. *IJEMS*, 2005.
[20] Patty Mechael. mhealth alliance: A history of mobile & mhealth. *mHealth Insight*, Nov 2012.
[21] mhealth share. mhealth fact sheet.
[22] Christopher Mims. In 2014 the next billion will access the mobile internetat $20 a handset. *Mobile Commerce*, Jan 2014.
[23] Kevin Priddy and Paul Keller. Artificial neural networks. *SPIE Press*, 2005.
[24] Daniel Shiffman. Neural networks. 2014.
[25] Greg Slabodkin. Global mhealth app services market to reach $26 billion by 2017. *Fierce Mobile Healthcare*, Mar 2013.
[26] Leslie Smith. An introduction to neural networks. Apr 2003.
[27] Statista. Forecast: number of smartphone users in the u.s. 2010-2018. 2014.
[28] Robert Gordon University. The back propagation algorithm. 2014.
[29] Neil Versel. Father of telemedicine: Take the exam room to patients. *Mobi Health News*, May 2013.
[30] Vivek Wadhwa. This indian start-up could disrupt health care with its powerful and affordable diagnostic machine. Nov 2013.

Appendix A
Reflection

Several courses come to mind when thinking of how previous work has helped my performance in this course. Perhaps the most obvious would be the initial programming courses (150 and 160) as well as the intermediate 200 and 230. Since without the programming knowledge acquired from them I would have been completely lost in terms of making any progress with my demonstration project for this course. The project was based in java which I learned quite well throughout all the course work of the computer science curriculum and featured data structures I had grown familiar with in 200. Using more specifics examples, the algorithm's course (338) helped in my understanding of the various algorithms used in training the neural networks, while having not having seen any of the algorithms covered in the course directly in this project, at least having some sort of familiarity with them allowed for a faster understanding of how they worked in comparison to someone who may be entirely new to the subject. Surprisingly, I also found the psychology courses I took to be beneficial in working on this paper. The ANNs related directly to how neurons function which was a topic I was all too familiar with from Perception, so translating that over to ANNs with weights and biases came as almost an entirely familiar subject. Focusing less on the material and more on the structure, my psychology courses also helped with this project as I had been previously exposed to lengthy research projects, just of a different subject matter. Regardless, they helped build more technical writing skills and how to phrase pieces which include heavy amounts of data. Earlier courses in my college career also contributed to this project going all the way back to First Year Seminar and several Philosophy courses I took. Both immediately introduced me to lengthy papers where it was necessary to organize material and build arguments in a coherent manner. Not to mentioned these papers also acted as practice for building my writing skills. Only after having written this is it interesting to see how influences from outside the department would aid such specific research in such a positive manner.

Appendix B
List of Figures