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A Critical Review for an Accurate and Dynamic Prediction for the Outcomes of Traumatic Brain Injury based on Glasgow Outcome Scale

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The world and every 5 min someone dies from Traumatic Brain Injury (TBI). Furthermore, it is a leading cause of death and disability in the world. Identification of patients with poor neurologic prognosis causes problem for the patients and their families. Presently, computer technology is increasingly been used and implemented in healthcare and predicting patient outcome can be useful as an aid to clinical decision making, explore possible biological mechanisms and as part of the clinical audit process. Machine learning, a branch of artificial Intelligence aims to make computer automated predictions more accurate. Neurologists need an accurate model to predict the neurologic outcome in patients with brain injury and this remains a challenge for the intensivist. A critical review on existing predictive models of traumatic brain injury is conducted in Science Direct, PubMed, Elsevier and Springer Link some other publishers. A review of related literature reveals that there is no method classified yet as being the perfect machine learning method. The review further shows that no prognostic models in TBI have yet been developed with proven results. In addition, it shows that predicting the outcomes of traumatic brain injury based on Glasgow Outcome Scale using machine learning methods is essential and needs to be improved.

Key words: Traumatic brain injury, accurate and dynamic prediction and Glasgow outcome scale

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INTRODUCTION

Traumatic Brain Injury (TBI) had been considered as human suffering since ancient times (Rajeswaran *et al*., 2012). Currently, traumas are critical worldwide problems related to health and one person dies from traumatic brain injury every 5 min (Fedorka and Sullivan, 2004). Furthermore, TBI has been the primary cause of fatality and disability in the world (Kim, 2011).

In Malaysia, TBI is a principal reason of death for people who are below 45 years old of age (Moppett, 2007). Automobile accidents are still the root reason for traumatic brain injuries. Based on statistics, the occurrence of road accidents is considered as one of the highest in the world. The death rate is approximately 22 deaths per 100,000 inhabitants (Liew *et al*., 2009).

In the Middle-East countries, TBI is once again the chief source of death and disability. Studies show that in Saudi Arabia 80% of fatalities in Ministry of Health Hospitals are due to TBI and the majority of them consist of youths. Overall in Saudi Arabia death occurring from TBI accounts for 17.4% and this is double the figure in USA which is only 8.3% (Bangash and Baeesa, 2010).

TBI is a severe health problem in USA and it takes place every 23 seconds (Goffus *et al*., 2010). The injuries in USA include skull and facial fractures and it occurs at an alarming rate of 180 to 250 per 100,000 people. Besides the fatal TBI, more than 1.5 million Americans endure non-fatal TBIs every year which do not necessitate hospitalization. Quite a large number (annual rate of 618 per 100,000 persons) sustain injuries that end up in a loss of consciousness but not serious enough to effect in long-term hospitalization. Intracranial hypertension, which might be a result from traumatic brain injury, is considered a most common cause of death in neurosurgery (Iencean, 2004). A sad point to note is that though many individuals suffer from brain injuries which do not require hospitalization but they end up with permanent disability (Nuwer *et al*., 2005). Schneider *et al*. (2002) assert that TBI result in more lasting deficiencies and higher death compared with other trauma cases.

Artificial Intelligence (AI) is the science and engineering of making intelligent machines. In other Words, Artificial intelligence is intelligent agents understands its environment and takes appropriate actions to succeed (Abghari *et al*., 2009; Curran *et al*., 2004; Vinayagasundaram and Srivatsa, 2007; Hui *et al*., 2011; Mpallas *et al*., 2011). In this information age, computer technology and in particular Artificial Intelligence (AI) plays an increasingly role in aiding healthcare and in predicting patient outcome (Bentaouza and Benyettou, 2010). El-Gohary *et al*. (2008) highlighted the importance of using artificial intelligence for decision making in medicine. Therefore AI can be useful in clinical decision making and in the process of clinical audit (Signorini *et al*., 1999a). Processing on medical dataset for clinical decision making is essential to help save time of both patients and doctors and to reduce the risk of wrong diagnosis (Fidele *et al*., 2009). Machine learning and its related algorithms is a major branch of artificial intelligence (Michalski *et al*., 1998; Michie *et al*., 1994; Mitchell, 1999; Shavlik and Dietterich, 1990). Machine learning algorithms in the early stages have been planned to scrutinize data pertaining to medicine. Presently, the concept of making a machine learn supplies quite a number of valuable tools for intelligent data analysis, data collection and data storage. Manual classification usually causes a mistake and getting a classification using a computer with accurate outcomes is a challenge for the computer scientist (Madhloom *et al*., 2010). Classification and prediction in medical diagnosis and prognosis are using increasingly (Blessia *et al*., 2011). The accurate prediction of clinical outcomes and diagnosis are very important for therapeutic decision making (Noorizad and Mahdian, 2006; Agyei-Frempong *et al*., 2010). Prediction plays a very essential role for evaluation of patients' outcomes (Dastorani *et al*., 2010). Basically in machine learning, patient records together with their accurate diagnosis are input into systems to generate an algorithm which could classify. Automated classification may help clinicians to diagnose at an early stage more efficiently and accurately (Britto and Ravindran, 2007). In this way, patient diagnosis can be speeded up, be more accurate and reliable. Furthermore, the classifier can be used to educate student physicians in arriving at an accurate diagnosis.

The advent of electronic computers in the sixties enabled modeling and analyzing large sets of data. So far, learning using symbols as explained through Hunt *et al*. (1966), methods using statistics as propounded through Nilsson (1965) and studies done by Rosenblatt (1958) on neural networks have so far materialized. These three branches created sophisticated methods and Michie *et al*. (1994) explain that they include pattern recognition techniques, using k-nearest neighbours, analysis using discriminants and classifiers using Bayesian concepts. In addition, other methods and techniques such as decision trees, rules, logic and artificial neural networks were used.

In the area of artificial intelligence, an expert system can be defined as a computer system that can make a decision similar to a human expert (Raju and Rajagopalan, 2007). To reduce and minimize elements of subjectivity, several computer expert systems were developed and integrated to help in the design of predictive methods. As an example, Electrocardiograms (ECGs) were created by making use of models derived from expert system (Bratko *et al*., 1989).

Detecting patients with inaccurate neurologic prognosis causes difficulties for the patients and their families (Beca *et al*., 1995). According to neurologists, time is a crucial factor in diagnosis and arriving at an appropriate decision that could aid the patients. Hence, accurate and timely prediction of neurologic results in patients with brain injury poses a challenge for the intensivist (Machado *et al*., 1999). Singh *et al*. (2007) assert that there is still no perfect machine learning model classified yet. Dynamically predicting the outcomes of TBI is still at an infant stage. This research aims to develop a predictive model using machine learning methods which when implemented could dynamically predict outcomes of Traumatic Brain Injury by overcoming the drawbacks and weaknesses of current machine learning models.

Traumatic brain injury: Traumatic Brain Injury (TBI), also known as intracranial injury, occurs when an external force traumatically injures the brain. TBI can be classified based on severity, mechanism (closed or penetrating head injury), or other features (e.g., occurring in a specific location or over a widespread area). The terms head injury, traumatic brain injury and acquired brain injury are often used interchangeably, but is refers to a broader category because it can involve damage to structures other than the brain, such as the scalp and skull.

TBI is a major cause of death and disability worldwide, especially in children and young adults. Causes include falls, vehicle accidents and violence. Preventive measures include the use of technology to reduce the impact resulting from vehicle mishaps (Cooper, 2011).

The after effects of brain trauma known as secondary injuries take place after the main impact had happened. These effects change pressure inside the skull and cerebral blood flow and lead to more serious damages compared to the first injury (Mogul-Rotman, 2011). As a result, a host of other emotional and behavioral side effects occur. Modern technology and the development of different therapies have helped in rehabilitation and in reducing TBI related deaths (McDevitt *et al*., 2012). Another adverse effect of TBI injury is that many victims exist in a vegetative state. Vegetative state patients normally appear to be wakeful by having open eyes but they do not reflect cognitive ability (Monti *et al*., 2010).

Causes of TBI: TBIs occur due to a number of reasons and in the U.S. they are primarily due to violence, road accidents and accidents at construction sites and in the sports arena (Faul *et al*., 2010). Road accidents involving motor cycles are a major cause and it is increasingly becoming significant as other types of causes reduce (Reilly, 2007). It is estimated that in the U.S. alone approximately 3.8 million TBIs occur due to sports activities (Sahler and Greenwald, 2012). Falls among children below the age of four and traffic accidents involving children are other common causes (Granacher, 2008). Hunt *et al*. (2003) show that injury resulting from child abuse is serious and it accounts for one-third of total injuries. Domestic brutality at home, work-related and industrial accidents are other causes of TBI (Bay and McLean, 2007; Comper *et al*., 2005). The use of weapons and bomb explosions are other primary causes of TBI during armed conflict between countries (Park *et al*., 2008).

Demographics of TBI: TBI occurs in more than 85% of traumatically injured children (Carli and Orliaguet, 2004). The largest occurrences of TBIs are found in persons whose ages are from 15 to 24 (Hardman and Anthony, 2002). Among youths, TBI injuries are common and the cost and loss of productivity is high too (Maas *et al*., 2008). The children from five to nine years and elders over 80 years are the most risk group (Rao and Lyketsos, 2000), and the highest rates of death and hospitalization because of Traumatic brain injury are in elders over 65 years (Brown *et al*., 2008). The incidence of TBI in First World countries is increasing as the population ages and the median age of people with head injuries has increased (Maas *et al*., 2008).

On a gender basis, it appears that more males suffer from TBI injuries compared to females (Hardman and Anthony, 2002 ; Rao and Lyketsos, 2000). Males account for two-thirds of childhood and youths head trauma (Necajauskaite *et al*., 2005). However, severity of injury in women is less than men (Moppett, 2007).

There is a co-relationship between socioeconomic status and TBI rates and people with lower qualifications and lower socioeconomic status tend to have more risk (Hannay *et al*., 2004).

History of TBI: Research studies show that dead injuries dates back to prehistory (High, 20 k to 05). Skulls found in battleground graves with holes drilled over fracture lines and this trepanation might be used to treat TBI in antiquity (Granacher, 2008). Ancient Mesopotamians knew of head injury and some of its properties, such as seizures, paralysis and loss of sight, hearing or speech (Scurlock and Andersen, 2005). The Edwin Smith Papyrus which was written in about 1650-1550 BC, defines different head injuries and signs (Sanchez and Burridge, 2007). Greek physicians including Hippocrates found that the brain is a center of thinking, and this understanding might come from their experience with head trauma (Levin *et al*., 1982).

From the 16th century onwards, doctors used the term concussion to explain about brain injuries (Zillmer *et al*., 2006). In the 18th century, doctors hypothesize that intracranial pressure is the cause of pathology after TBI instead of skull damage. Thus, in the 19th century, surgeons relieved pressure in the brains by opening the skull (Granacher, 2008).

Studies done by Corcoran *et al*. (2005) showed that there was a correlation between TBI and the mental illness. In the 20th and 21st century, technology played an important role by providing tools for diagnosis. New tools such as imaging tools, CT, MRI and Diffusion Tensor Imaging (DTI) provided better patient diagnosis and treatment. In the 1950s, the intracranial pressure monitoring has been introduced and this can be called as the modern era of head injury (Marshall, 2000). The mortality rate of TBI was high and rehabilitation was uncommon.

Hundreds of people suffered from brain injuries as s result of using explosives during World War I. More research studies were made and brain injuries were categorized into primary and secondary brain injuries. After World War I, the death rate reduced and made rehabilitation possible (High *et al*., 2005). Actually, the explosives used in World War I caused many blast injuries and a large number of TBIs that resulted allowed researchers to learn a lot more about TBI (Jones *et al*., 2007; High *et al*., 2005). In addition, a great deal of progress has been made since then in brain trauma research such as the discovery of primary and secondary brain injury (Marshall, 2000).

Glasgow outcome scale: Patients who had undergone TBI can be categorized according to the degree of residual disability. The Glasgow Outcome Scale (GOS) rates patient status into five categories. They are namely Dead, Vegetative State, Severe Disability, Moderate Disability and Good Recovery (Jennett and Bond, 1975). Death is the long-lasting termination of all biological functions that sustain a living organism. Vegetative State implies that the patient is unresponsive but alive. Vegetative State (VS) patients are still not recognized by law as death in any legal system. In the case of severely disabled, the patients are conscious but the patient relies entirely on others for daily support. Patients who are moderately disabled are independent but are still disabled. In the case of Good Recovery patients, the patients have started many of the normal activities but may still have some minor residual problems. A more elaborate classification was done by the Extended GOS which classifies TBI patients into 8 divisions namely Death, Vegetative state, Lower severe disability, Upper severe disability, Lower moderate disability, Upper moderate disability, Lower good recovery and Upper good recovery (Maas *et al*., 2007).

A CRITICAL REVIEW ON PREDICTING OUTCOMES OF TBI

A critical review on existing predictive models of traumatic brain injury is conducted in Science Direct, PubMed, Elsevier and Springer Link some other publishers. The existing predictive models of traumatic brain injury are presented in Table 1. The accuracy of the predictive model and whether it can achieve the accurate and dynamic prediction are shown.

In nutshell, many research studies have been done on predictive models of traumatic brain injury. Detecting patients with inaccurate neurologic prognosis causes

Table 1: A critical review on predicative models of traumatic brain injury

Author(s) and Year	Cit.	Title	Predictive Model	Accuracy	Dynamic prediction	Accurate prediction
Pignolo and Lagani (2011)	Not cited	Prediction of Outcome in the Vegetative State by Machine Learning Algorithms: A Model for Clinicians?	C4.5 SVM NB K-NN	AUC of C4.5 = 0.84 AUC of SVM = 0.81 NB = 0.91 K-NN = 0.88	×	×
Rughani *et al*. (2010)	5	Use of an artificial neural network to predict head injury outcome	ANN	Sens. = 87.8 Spec. = 72.4%	×	×
Ji *et al*. (2009)	12	A comparative analysis of multi-level computer-assisted decision making systems for traumatic injuries RBF ANN	Logistic AdaBoost C4.5 SVM	Logistic 72.9% AdaBoost 73% C4.5 75.2% CART 77.6% SVM 79% RBF ANN 79.04%	×	×

Table 1: Continue

Author(s) and Year	Cit.	Title	Predictive Model	Accuracy	Dynamic prediction	Accurate prediction
Guler *et al.* (2009)	4	Evaluating of traumatic brain injuries using artificial neural networks	ANN	91%	×	×
Pang *et al.* (2007)	23	Hybrid outcome prediction model for severe traumatic brain injury	DT LR BN ANN	ACC of DT = 73.10% ACC of LR = 70.51% DA 69.39% BN 65.67% ANN 63.38%	×	×
Schreiber *et al.* (2002)	90	Determinants of mortality in patients with severe blunt head injury	LR	AUC= 80.5%	×	×
Li *et al.* (2000)	56	Neural network modeling for surgical decisions on traumatic brain injury patients	LR RBF MLP	AUC of LR = 0.761 AUC of RBF 0.88 AUC of MLP = 0.897	×	×
Sakellaropoulos and Nikiforidis (1999)	15	Development of a Bayesian network for the prognosis of head injuries using graphical model selection techniques	Bayesian Network	ACC = 69%	×	×
Choi *et al.* (1991)	168	Prediction tree for severely head-injured patients	Decision Tree	ACC = 77.7%	×	×
Signorini *et al.* (1999a)	189	Predicting survival using simple clinical variables: a case study in traumatic brain injury	Logistic Regression	ACC = 90%.	×	×
Signorini *et al.* (1999b)	95	Adding insult to injury: the prognostic value of early secondary insults for survival after traumatic brain injury	Logistic Regression	Not Mentioned	×	×
Andrews *et al.* (2002)	113	Predicting recovery in patients suffering from traumatic brain injury by using admission variables and physiological data: a comparison between decision tree analysis and logistic regression	Decision Trees	ACC between 60-96%	×	×
Combes *et al.* (1996)	44	Severe head injuries: an outcome prediction and survival analysis	Logistic regression	Internal AUC = 0.87 External AUC = 0.73	×	×
Hukkelhoven *et al.* (2005)	126	Outcome after severe or moderate traumatic brain injury: development and validation of a prognostic score based on admission characteristics	Logistic regression	Internal AUC Between .80–.81 External AUC Between .83–.89	×	×
Sakellaropoulos and Nikiforidis (1999)	15	Development of a Bayesian network for the prognosis of head injuries using graphical model selection techniques -Google Scholar	Two Bayesian networks	ACC of Network 1= 81% ACC of Network 1= 69%	×	×
Schreiber *et al.* (2002)	90	Determinants of mortality in patients with severe blunt head injury	Logistic Regression	AUC 5 .81	×	×
Li *et al.* (2000)	56	Neural network modeling for surgical decisions on traumatic brain injury patients	Logistic regression and RBF ANN	Logistic regression Sen. =0.73 and Spec.= 0.68 RBF ANN Sen. = 0.88 and Spec. =0.84	×	×

difficulties for the patients and their families (Beca *et al*., 1995). According to neurologists, time is a crucial factor in diagnosis and arriving at an appropriate decision that could aid the patients. Hence, accurate and timely prediction of neurologic results in patients with brain injury poses a challenge for the intensivist (Machado *et al*., 1999). As it has been presented in (Table 1), there was no study has yet to be made on dynamically predicting the outcomes of TBI. In addition, different machine learning methods give different accuracy with the same dataset. Existing models have conflicting issues and therefore it is pertinent that a new model of dynamically predicting the outcomes of TBI need to be developed.

CONCLUSION

Predicting of TBI outcomes studies are significant as it can help doctors to make an accurate clinical decision and explore possible biological mechanisms as part of the clinical audit process. In addition, it can help to train students or physicians who are non-specialists to diagnose patients. The review shows that existing machine learning methods provide different accuracy using the same dataset. A review of related literature reveals that no predictive models in TBI have yet been developed with proven results. In addition, there was no study has yet to be made on dynamically predicting the outcomes of TBI.

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