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A Clinical Prognostic Framework for Classifying Severe Liver Disorders (SLDs) and Lungs' Vulnerability to Virus

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ABSTRACT

Most severe liver diseases (SLDs) are attributed to increased risk for cancer, and cirrhosis, through which the manifestation of fibrotic tissues and scars tends to affect liver function The role of liver is indispensable, as inner organ performing services that ranges from metabolism, immune guide, energy producer and digestive aid, just to mention a few. Prevalence of classification problem and the need for automated prognosis is the continual drive to apply data mining techniques and/or machine learning algorithms in medical diagnosis and clinical support systems. Computational scientists and researchers in the field of artificial intelligence have recorded notable efforts with existing methods/models for diagnosis or prognosis, yet their effectiveness and functional performance is not without drawback due to ambiguity of medical information and selected features in patients' data to tell the future course. In this paper, a novel hybridized machine learning model was provided (Fuzzy c-BC) for clinical classification of Severe Liver Disorders (SLDs) and to determine Lungs Vulnerability (LV) to virus; by incorporating individual strength of fuzzy cluster means (FCM) and naive Bayes classifier (NBC) for projecting future course of every categorized liver disease (LD) and its implication to aggravate lungs infection if preventive measures are not taken in timely manner.

Keywords: Novelty, Model, Prognosis, Virus, Liver, Lungs, Clinical Decision

1 Introduction

An inflammation of liver tissues at a later stage or critical condition is a global catalyst to cancer related death. The role of liver is indispensable, as inner organ performing services that range from metabolism, immune guide, energy producer and digestive aid, just to mention a few [1]. Liver disease refers to

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various unhealthy situations, conditions, and infections that disturb the functional states of the liver [2]. Any irregularity resulting from liver function test (LFT) and yellowish discoloration of the skin are typical traits of liver disorder. Computer-aided modelling and decision analysis tools in knowledge domain or particular field of endeavour had continue to evolve by on-going researches [3]. Development of intelligent system that exhibit those features associated with human experts like learning process, understanding, reasoning and problem solving is now germane to public health.

Medical diagnosis of liver disorder or chronic liver diseases involves analysis of blood albumin commonly called enzymes level in the blood, as well as liver function test (LFT). The use of blood test to unveil the functional state of human liver is highly paramount, based on clinical specification of the target patients [4].

Furthermore, lungs and liver are inseparable biological constituents in human body because lungs are upper abdomen organs within the cardiac sac that extracts oxygen from fresh air. Liver is just at the left position below the lungs, and its acts as blood filter in order to perform filtering of chemicals and associated impurities that may result from drugs and contradictive medications. In view of the above, untreated liver disease which is no longer mild will definitely manifest in lungs disorder, thereby making lungs more vulnerable to virus infection [5].

Virus can be deadly like bacteria on weakened immune system, and microscopic in nature due to its non cellular structure. It is contagious and could spread so fast among people through body fluid, use of contaminated sharp objects, blood transfusion, and physical contact [6].

Recently, corona virus appears as global epidemic which kills so quickly and responsible for huge number of casualties in hospitals and medical centres across the universe. Its epidemiological reference is COVID-19, being a respiratory ailment and infectious disease yielded novel illness that is universally disastrous as it defies all known therapeutic measures and/or diagnostic solution at the moment. It actually emanated from Wuhan City, in Huber Province China. Every infected person goes for immediate self isolation in furtherance to, and imperative approach to overcrowd quarantined. World Health Organization (WHO) recommended safety measures, which is quite inevitable to contain further spread of this virus.

However, fuzzy cluster means (FCM) and Naive Bayesian Classifier (NBC) performs better in isolation from previous researches and in different context; while fuzzy cluster means (FCM) seem efficient in handling the ambiguities in clinical data; naive Bayesian classifier (NBC) is effective and powerful for classifying large dataset. Similarly, prognostic chain should be tailored towards clinical decision support to determine vulnerability of lungs to infectious viruses. Hence, the need to incorporate individual strength of duo techniques as hybrid machine learning for projecting future course of every categorized liver disease (LD) and its implication to aggravate lungs infection if preventive measures are not taken in timely manner.

2 Related Work

Self organizing maps (SOM) of Neural Network and K-means algorithm are commonly used to group database into different classes of like-points. The duo uses visualization pattern by quantization vector which allows sample vector to maintain low-dimensional grid in an arranged pattern, as k-means algorithm handles clustering and classification perspective through unsupervised learning approach [7]. A universal approach to optimization was leveraged upon for classifying the symptoms of breast cancer; having trained the breast cancer data to build a functional knowledge base for diagnostic systems with accurate performance [8]. The reported technique yielded an intelligent solution that determines the clusters' focal point; space and duration required as storage and execution parameter depends largely on the dimension of problem domain.

Support Vector Machine (SVM) as a supervised learning technique for classifying and establishing the extent of relationship in predictive scenario. However, Naive Bayes classifier produced good classification with a desired improved performance when applied to clinical dataset for liver disorder [9]. Comparative analysis of predictive and extraction rule methods with the use of rough sets for liver disorder diagnosis was carried out by [10].

Consequently, the outcome of findings relates classification efficiency of any machine learning algorithm to the dataset attributes being captured. Also corroborated the fact that a particular sign or symptom can be associated with two or more clusters or disease categories; and as such the consideration for fuzzy logic or fuzzy system of predictive task is justified due to complexity of clinical data and medical history of most patients as experimental subjects [11]. Developed a knowledge base system for diagnosing liver diseases using fuzzy cluster means (FCM). It used a rule editor of fuzzy inference to establish diagnostic decision by type matching individual symptom with the cause. Cased based reasoning for medical diagnosis was provided with performance accuracy of sixty-five percentage. Machine learning algorithm has been used previously for disease classification in comparison perspective, its projection of hybrid model expects to produce prediction accuracy [12]. Multi-layer inference mechanism was inculcated in adaptive neuro-fuzzy system for classifying data for liver disorders; though its detection reliability for ailment of the liver was not really considered [13].

Designed adaptive neuro fuzzy inference for analysing liver cancer (ANFIS) based on computed tomography (CT), meanwhile two-dimensional images (2D) might not be appropriate for model fitting, and towards achieving optimal performance [14]. Hybrid ANFIS had proved its usefulness and relevance for liver disorder diagnosis; hybridization approach allows particle swarm optimization (PSO) to be amalgamated with adaptive neuro fuzzy inference (ANFIS) even when the experimental design seem not sustainable [15]. Applied computational automation to the diagnosis liver disorder through multilayer neuro fuzzy technique. Its diagnostic efficiency was established through subjective human experience by taking clinical attributes of patients as input variables; which were trained to sample testing in order to determine output variable by neuro fuzzy pattern classification. This is similar direction with, except that their finding was a novel model using deep learning capability of neural network for predicting chronic diseases [16].

Designed a cost-effective diagnostic system for liver diseases using fuzzy logic and blood count as functional mechanism. Mandani inference engine takes blood constituents like haematocrit and thrombocyte as input variables in order to produce outputs relating to infection fight and anaemia. Adaptive neuro fuzzy also produced similar result when back propagation layer of neural network is being triggered for reasoning [17]. Developed a neuro fuzzy based system for classifying liver disorder [18]. This system inculcates logical framework for clinical decision making by leveraging on the fuzzification and defuzzification modality of fuzzy logic to handle vague and unstructured clinical dataset. Though performance evaluation was not made available in their report, yet interoperability of its implementation tools allows production of meaning clusters. While Visual Basic was used to design the front end, Microsoft Access was used for the back-end application. Feature selection and reduction for liver disease was equally handled by particle swarm optimization (PSO) algorithm. Optimality of selected features was enhanced by performance and functionality of the model with proactive segmentation as shown in figure 1.

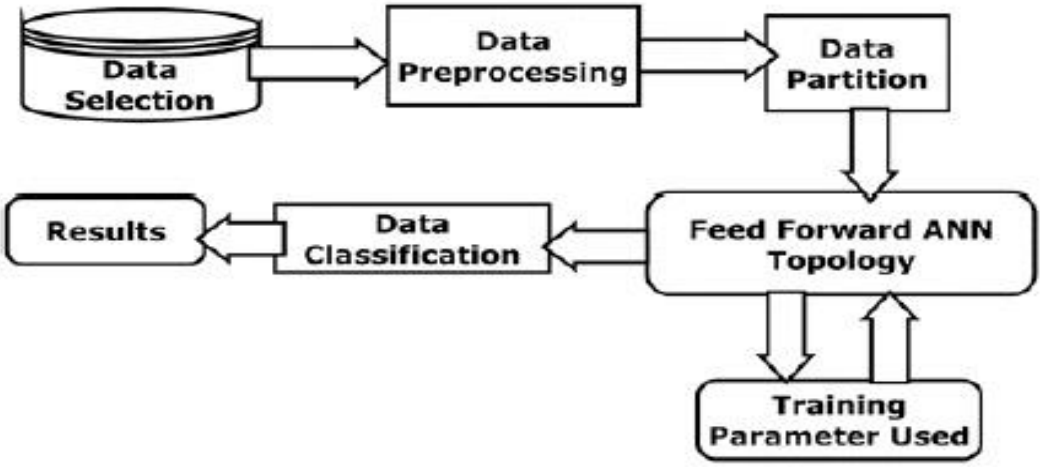

Fig. 1: ANN–PSO Model for Feature Selection [19]

Machine learning approach to the liver disease prediction in vulnerable patients, probabilistic nature of support vector machine (SVM) and k-nearest neighbour (KNN) were dependants of statistical learning theory for clinical feature in their work [20]. Support vector machine (SVM) and fuzzy logic had been previously used together for accurate estimation of group classification [21]. Leveraged on the dynamism and optimistic tendency of hybrid whale for simulated annealing. It is a non-invasive evaluation of chronic liver disease by ensemble classification as shown in figure 2.

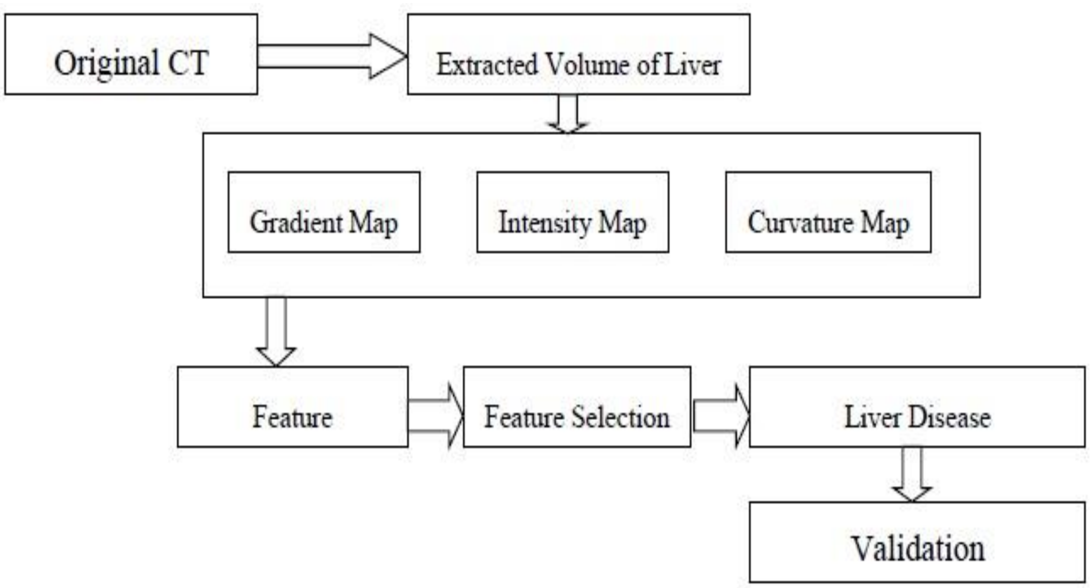

Fig. 2: Hybrid Whale Model for Liver Disease Diagnosis [22]

3 Methodology

This paper adopts quantitative and developmental approach by inculcating fuzzy cluster means (FCM) as class partitioning and segmentation algorithm; and the use of naive Bayes classifier (NBC) for predictive projection analysis in hybridized machine learning model. The model was designed as logically synchronized and juxtaposed mechanism for functional prognostic entity. Model optimization was ensured with feature selection and parameter tuning for real input and output target, to avoid costly and subjective sampling error.

3.1 Radiographic Sensors in Liver Functional Testing

The maker and model of numerous sensors which are commercially available and medically used for ultrasound scan, and to produce radiographic images for liver function test or computed blood count usually inculcate electromagnetic and electromechanical components. Most of them are particularly attached to diagnostic equipment and/or biomedical gadgets so as to initialize the control, perform extraction of sample feature and analyze matching signal.

Fig. 3: Radiographic Sensors for Liver and Cardiac Test [23]

3.2 Clinical Evaluation and Diagnosis of Liver Disease

Medical routine for diagnosing liver disorder (LD) involves critical assessment of manifesting signs which prompts consulting endocrinologist or physician to perform clinical evaluation through physical examination of patient's body, liver function test to check the liver enzymes in the blood, ultrasound verification, radiographic imaging or computed tomography (CT).

The recorded complaints as presented and/or attributed to major symptoms being manifested on patient will be cross examined to rate their likelihood tendency in nominal / ordinal pattern in order to match evident possibilities with a particular illness or type of liver disorder. In some cases, interactive session could be established with the patient at a consulting room of the clinic through interview in order to document the situations that could account for patient's ailment.

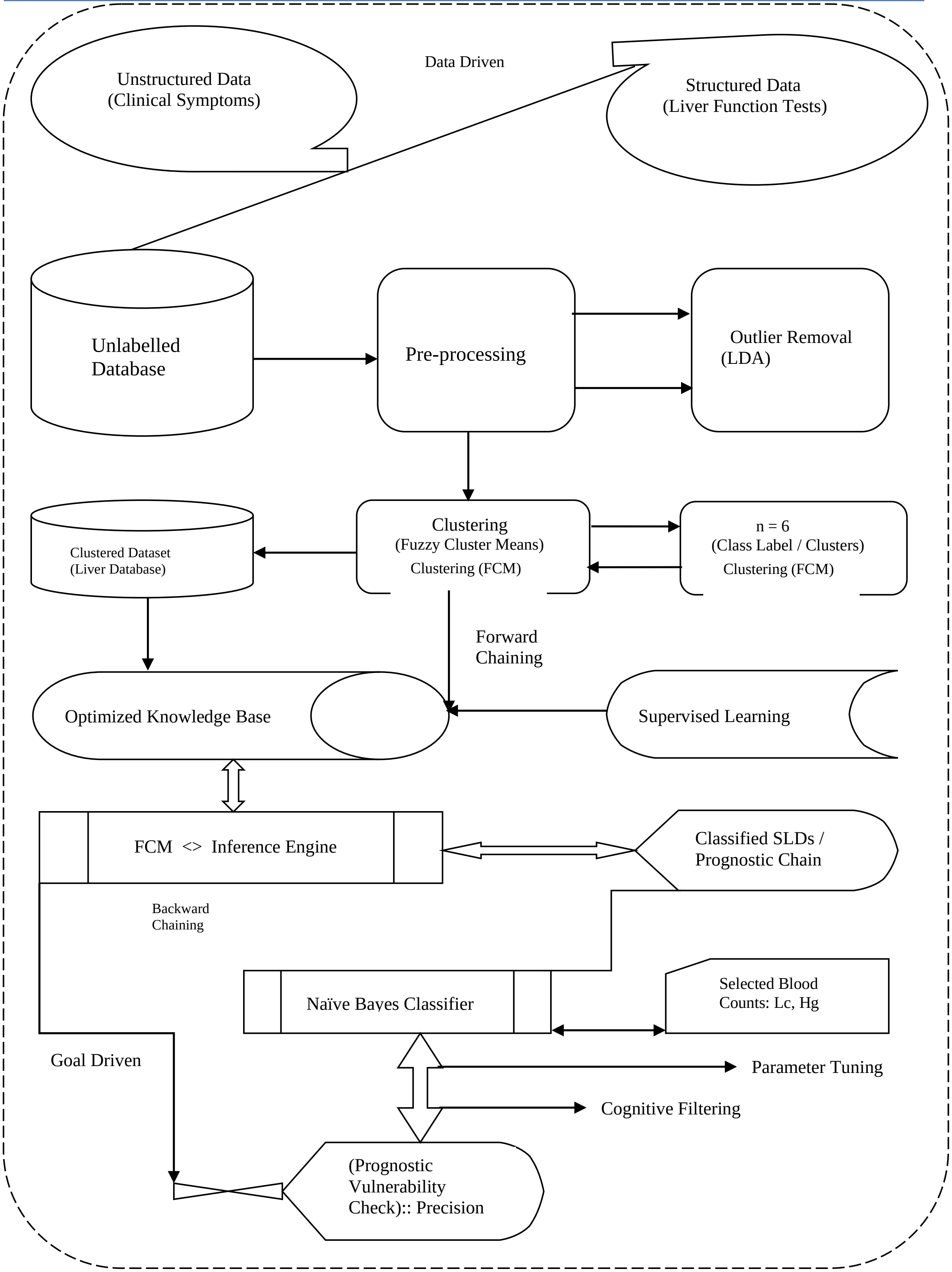

Fig. 4: Architectural Design for Novel Clinical Prognostic System (Fuzzy c-BC)

4 Functional Approach of Novel Prognosis

Enzymes in the blood commonly called 'albumin' and clinical information were used to define input variables for inference mechanism of fuzzy rule editor while liver ailment is being identified by the target output variables, which do not only classify sample liver data into healthy and diseased classes but can explicitly build infinite clusters by segmenting the patients' data to specify the type of liver disorder. The goal is to subject target output to two-phase estimator by utilizing it in conjunction with selected blood count like 'leukocytes' and 'haemoglobin' as input for multiclass integrated classifier to determine lungs vulnerability.

A novel Fuzzy cluster - Bayes classifier (Fuzzy c-BC) was designed not just to determine if a patient has liver disease or has been affected by liver disorder using clinical dataset, but to also classify his/her type of liver disorder to appropriate cluster. Two-phase verification and/or cross validation of target variable was conducted by turning the previous output from clinical prognosis stage as input for decision support stage. Unstructured and structured data being fuzzified with fuzzy logic refers to attributes of clinical evaluation and liver function test (LFT) reports previous merged as combined features.

The previous output which is a classified liver disorder was complemented by selected blood counts: 'leukocyte' and 'hemoglobin' as input variables for decision support layer which is handled by another machine learning algorithm called Naïve Bayes classifier (NBC). Liver dataset has six (6) attributes (conditional features). From these six (6) conditional attributes, five (5) attributes represented the outcome of medical examination, while the rest of the attributes is for chemical examination. The dependent variable or target output is the major class variable.

Class variable as target output indicates the type of liver disorder that an individual has based on symptom intensity from preliminary clustering / classification into specific type of liver disease. But, at final prognosis and decision support class variable or target output indicates whether a classified liver disorder or identified severe liver ailment makes lungs vulnerable to virus or not in the given patient; having utilized selected blood counts as clinical parameters for more input.

5 Conclusion

Early detection of liver disorder and peculiar classification of disease type is a catalyst to timely clinical decision; aiding quick recovery and cost-effective treatment. Continuous inflammation could lead to scarring of liver tissues by partial or complete liver dysfunction, thereby causing medical complication with subjective human experience in convectional clinical diagnosis. Limited yardstick was commonly adopted for measuring performance of any model, method or technique provided for diagnosis and prognosis of liver related diseases. Two categories of output or predictive variables have been the major classification target of existing systems as presence or absence, healthy and non healthy, normal and diseased without approximating the intensity level. Hybridized models and/or machine learning algorithm have been projected for improved accuracy in diagnostic performance due to deep learning and scalability tendency, because it combines the reasoning potential of duo techniques in unique framework.

Ethical Approval: Yes

Informed Consent: Yes

Competing Interests:

The author declared that no conflict of interest exists.

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