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ONTOSkDS: Clinical Decision Support System for Skin Diseases using Ontology and Hybrid FNN

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ABSTRACT

Among all of the skin diseases, Erythematous-Squamous Disease (ESD) is considered as the most complex one. It comprises of six types namely pityriasisrubra, lichen planus, chronic dermatitis, psoriasis, seborrhoea dermatitis and pityriasisrosea. The primary reasons for inconsistent diagnosis are the common morphological features; this also makes the diagnosis stringent. ESD diagnosis is tremendously challenging, as it is not only based on the inculcated visible symptoms but also the physician's expertise. A major factor for the evolution of Clinical Decision Support System (CDSS) is to integrate dermatology and medical software as it is an essential aspect of speciality-specific ontology. Ontology aids in defining the semantics of the data and knowledge in a more formal way. It also helps in encoding the domain knowledge naturally for data mining purposes. For modelling high-quality, linked and coherent data, ontology plays a vital role. Ontology's role in the health care industry helps people to analyse the nature of the diseases and helps to treat them. To get high accuracy diagnosis and reduce error rate a Neural Network (NN) is used for modelling, NN is considered as the most powerful one for which relationship between data is unavailable and for the data that are imprecise and noisy. Fuzzy logic gives flexibility for reasoning, which makes it probable to consider the inaccuracies and uncertainties. A fuzzy rule explicitly says that both the premise and the consequent are true to the same degree of the membership function. The Hybrid Fuzzy Neural Network (FNN) obtained 99.4% of accuracy compared with existing work. Semantic Web Rule Language (SWRL) that merges Web Ontology Language (OWL) ontology's to rule-based applications is achieved with the help of SWRL. Then the Semantic Query- Enhanced Web Rule Language (SQWRL) can easily be used by SWRL to obtain the relational structure for the ONTOSkDS with DROOLS inference engine.

Keywords: CDSS, Ontology, Fuzzy Neural Network, SWRL, SQWRL, DROOLS.

INTRODUCTION

The health care industry helps in providing the goods and services to treat patients with the utmost care. Health care is one of the fast-growing industries. It was known that 14.3 million people are engaged concerning the health industry - Bureau of Labour Statistics. Health care plays an enormous part in the country's economy. [1] About the health issues, skin disorder forms the major problem faced by the people despite many other diseases. Especially in ESD, it is essential to diagnose and treat patients at the earliest. [18]

Various techniques are available for the classification of ESD [2] to create the structure of the ontology. Support Vector Machine (SVM) is most commonly used in clinical support system. [3] Improved SVM produce better results when compared with the classical SVM [14]. Ontology consists of various concepts that hold in a specified domain and the relationships that exist so that formal specification of the knowledge can be

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obtained easily. Parts such as objects, classes, relations, attributes, rules and axioms are to be explicitly mentioned. Other than introducing the knowledge that can be often used, Ontologies also help in including the domain knowledge [4] [19]. Ontology shares users with the necessary structure so that information is linked with other pieces of information on the Web of Linked Data as they are used to specify common modeling representations of data from distributed, heterogeneous systems and databases [5].

In this modern world, there are situations where people are unable to say YES or NO despite having vast information. To solve this ambiguity, fuzzy logic is used. Classification with non-linear characteristics is easily achieved using fuzzy logic. It is capable of handling the data with uncertainties. The fuzzy system can be matched to any kind of input and output data and also conventional control techniques can be merged. Fuzzy Logic (FL) is a reasoning method that resembles human reasoning [6].

To make the system work more like humans, we may incorporate the fuzzy logic into neural systems. This overcomes the problem of knowledge acquisition. Neural network learning techniques automate the process of designing the membership functions which quantitatively define the linguistic labels and also helps in reducing the time and development cost while improving the performance [13]

Neural networks are often referred to as Artificial Neural Networks (ANN). They are computational models containing processing units which help in communication through the signals. Keeping the human brain as base these ANN were developed. These are commonly used for developing when the data is uncertain and at times with noise. ANN is used in various fields from agriculture and technology. The ultimate reason for the success of ANN is that it can learn and improve the performance of the model through learning. [7]

The most dynamic way to represent various interrelated data is by representing it graphically. The development of the graph-oriented system and graph-based datasets originated because, domains like social networks, biological sciences, multimedia, and geography [15] predominantly represents its information graphically. This paper focuses on various prominent approaches for graph data management: Resource Description Framework (RDF) databases. The query linked data are stored in RDF database systems is also known as triple stores, it is specifically designed for this type of storage and these systems follow Semantic Web standards, particularly RDF [16] [17].

Semantic Web Rule Language (SWRL) is used to define the rules and the corresponding logic for the Semantic Web. SWRL is considered as the rule language of the Semantic Web. The Semantic Web Rule Language (SWRL) is defined with the help of OWL-based language. To develop more powerful reasoning capabilities, SWRL uses OWL concepts. To query the OWL ontologies SQWRL (Semantic Query-Enhanced Web Rule Language) is widely used [8].

SWRL Bridge acts as an essential catalyst in integrating the protégé OWL and the DROOLS Rule Engine. DROOLS engine constitutes of rule base, fact base and execution engine, also it is a java based rule engine. DROOLS, in general, produces a high-level performance execution, and while it is free of charge for the academic users a minimal cost is involved for non-academic users. DROOLS has the flexibility to allow users/developers to make custom changes for complex design, also DROOLS supports when/then format and it is a forward-chaining inference engine[18].

LITERATURE SURVEY

This research paper proposed a method for combining common measures of various categories even without ontology instances. While using the semantic web, Ontology helps in giving formal details of the concepts and relationships. For communicating between similar ontologies it is needed to explicitly mention ontologies characteristics. Because of concept properties in a particular domain, it is easy to have similar ontologies. Different algorithms like K-Nearest Neighbour (KNN), Decision Tree (DT), SVM and AdaBoost classifiers are utilised for handling heterogeneous ontologies. Low cost and better classification rate are optimized for each classifier.

From the experimental results, it was found that the F-measure criterion increased to 99% when used with the chosen feature and right classifiers. Also, results indicated that it is highly comparable and overcomes the existing values of F-measures. [9]

In this paper, the author presented a fuzzy ontology for summarizing the news. The fuzzy concepts are further extended for study based on crisp concepts of domain ontology. It is easier to explain knowledge than domain ontology to solve many uncertain issues in real-life situations. Initially, domain experts predefine the various events with domain ontology. The document pre-processing mechanism helps in generating related terms using news corpus as defined by the domain expert. Later term classifier classifies meaningful terms using news events. The membership degrees of fuzzy are generated with the help of fuzzy inference mechanism. Each fuzzy concept has corresponding membership degrees that are related to the domain. For news summarization, the newsagent is developed with fuzzy ontology. For news summarization five modules such as retrieval agent, the pre-processing mechanism for the document, and extractor for sentence path, generator and filter for particular sentence are used. Then the experimental website is constructed to analyse the newly proposed concept. The results indicate that news summarization using fuzzy ontology is more effective than the traditional [10].

The article intends to brief the domain with the self-learning algorithms with the help of the fuzzy ontology and from text corpora. Knowledge acquired with the help of the fuzzy ontology is discussed along with the set of SWRL rules (Semantic Web Rule Language). The concepts explained are validated with the results on ontology self-learning and a comparison study of inference algorithms was performed with the help of the developed algorithms. [11]

In recent days commonly discussed topic is enhancing Semantic Web technologies to deal with uncertainty and imprecision. SWRL aids in giving extra benefits to OWL technologies while fails in handling the uncertainty or imprecision. SWRL-F is formed to enhance the SWRL rule language and semantic foundation. To use fuzzy reasoning SWRL-F ontology is widely used. The language formed is highly efficient with because of the fuzzy operations which do not produce any changeableness. [12]

METHODOLOGY

The ESD data set which is having 34 features is processed with the help of improved SVM to get the classified results for diagnosing the people with skin disorder [14]. Feature selection in the developed model using Improved SVM may not lead to a solution with high accuracy. The objective of this research is to design and develop disease ontology with high accuracy for CDSS.

To reduce the error rate and obtain the optimal result in diagnosing at a higher rate the model is developed with the following phases as shown in Figure.1.

1. Applying Fuzzy logic
2. Generation of fuzzy rules
3. Neural network
4. Using RDF, SWRL and DROOLS to get the optimized structure
5. ONTOSkDS for CDSS

Applying fuzzy logic

In this phase, the algorithm is designed by integrating fuzzy set-theoretic concepts. To express the data of linguistic values, fuzzy logic is used. This helps in rendering the formal description of concepts. To handle the imprecision and uncertainties fuzzy variables play a vital role. Fuzzy Logic helps in reasoning the system. A fuzzy system is made up of a Knowledge Base (KB) and an Inference Mechanism (IM). Fuzzy Rule Base (FRB) and a Fuzzy Databases (FDB) are in KB. The rules which form the core of the system are usually stored in FRB. The rules in FDB are used for constructing the fuzzy sets with the help of the attributes. IM uses FDB and FRB to classify new examples. In this work, ontologies are merged with objects (stored in a database) to identify documents semantically for the corresponding user’s query. It is clear that on introducing fuzzy ontology the information retrieval is improved.

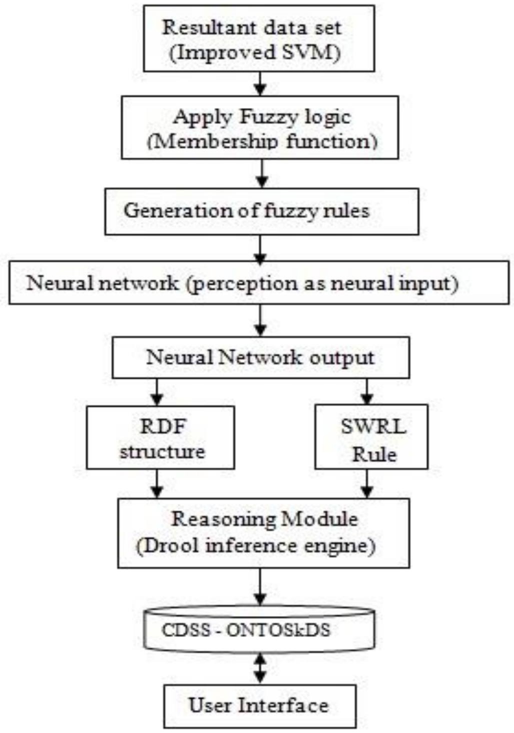


Figure.1: Proposed Flow Diagram

Generation of fuzzy rules

Here fuzzy classification systems are done with the help of the fuzzy sets and partitions for granulating the domain feature. The features are represented with the help of the linguistic variables in the antecedent part and class for the consequent part. All the attributes and records are considered for generating membership value and fuzzy rules. In this research, triangular membership functions are implemented to represent fuzzy sets due to its nature of ease, simplicity and efficiency. Each feature can be of a fuzzy number and split into three parts namely Low, medium and high using fuzzy membership value. Hence the Fuzzy rules are created by considering each record and the value is replaced either into high, medium or low based on the fuzzy membership value. The obtained rules are applied to the neural network.

Neural network

Neural Networks (NN) and Support Vector Machine (SVM) are amazing Soft Computing techniques used for analysing the functions, pattern recognition and to predict the outcomes. In the neural network, the pre-processed dataset is given to the input layer. NN contains some form of 'learning rule' which modifies the connections according to the input pattern associated with it. In the hidden layer, weights are calculated. With the help of the weighted value, the fuzzy membership value and fuzzy rules are generated. The rule set is then given to SWRL for further processing. The pseudo-code of the proposed Hybrid FNN is shown in Figure 2.

RDF and SWRL with DROOL

Ontology renders services to both user and system so that they can easily access with the help of the common domain. The classification results are given to the Resource Description Framework (RDF) to create a structure of skin disease ontology and then given to the SWRL. The query is created for the defined class which helps in segregating the details of the patients. Ruleset (query) is then created for the corresponding class.

These queries created are then passed to the SQWRL to process the queries and the structure is obtained for each patient with all related details.

```
Input: Skin Disease dataset Di....Dn;
Output: Neural Network Classifier NN
1. Weights are initialized in the network random dataset Di... Dn,
Hidden Neurons weight Wi......Wn (random), bias b
2. While (di! = null)
            for each samples D do
2.1 Ot = output of the network   (network, D);
2.2 To = trainer result for S
            2.3 Calculate error (To - Ot) at output unit
3. Compute all Neuron weight in the hidden layer and then pass to the output layer
y= ∑ (weight * S) +b
z= (D1*W1 + D2*W2 + D3*W3 +.........+ Dn*Wn)
Activate function
Sigmoid (z) =1/(1 + e^(-z))
Backward pass
4. Calculate delta-wi for all associated weights in the input layer backward pass continued
5. Network weights are updated
            End while
6. Until all samples are classified correctly or stopping criterion satisfied
            Return (step 1)
```

Figure.2: Pseudo Code

A **Drools** is the Rule **Engine** which utilises the approach built on rules to decouple the system. The decision making results when applied to the system in the form of the rules. For executing and processing the business rules, the rule engine is used.

ONTOSkDS for CDSS

Once the skin disease dataset was fed to Ontology platforms to create RDF/OWL structures, rules were generated in SWRL. Rules from SWRL when passed into the inference engine create a CDSS that offers support in providing classification, documentation, storage and retrieval of the ESD dataset. The user interface used by healthcare professionals can access such data through this proposed CDSS model to diagnose ESD accurately. The CDSS model based on Ontology is illustrated in Figure 3.

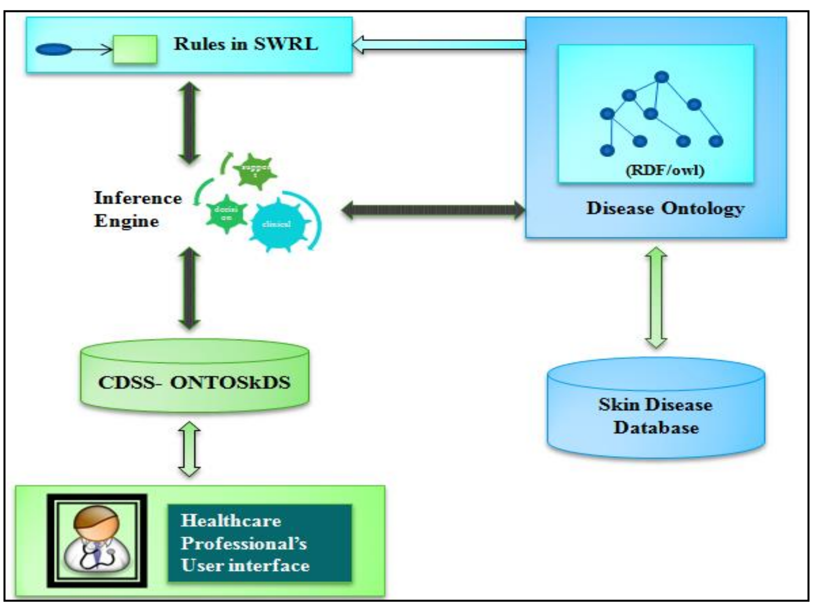


Figure.3: CDSS- ONTOSkDS Framework

EXPERIMENTAL RESULT

The experimental results of Hybrid FNN are compared with the existing ISVM [3] and FNN [20]. Precision, recall, F- measure, accuracy and error rate are the metrics of the classification results.

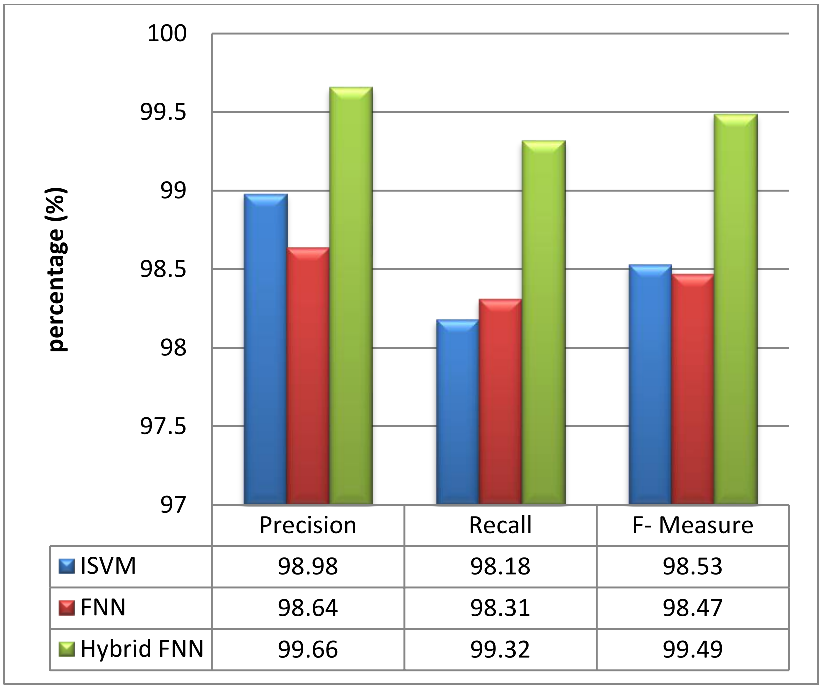
Precision

Precision is described as a calculation of exactness or quality. Also, higher precision describes that the methods given back meaningfully are more significant outcomes than unrelated. The precision (Figure .4) is given by $\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$

Recall

The recall is the degree of true positives separated via the over-all amount of elements, which efficiently be owned by the positive class. The recall (Figure .4) value is calculated in this way:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$



	Precision	Recall	F- Measure
ISVM	98.98	98.18	98.53
FNN	98.64	98.31	98.47
Hybrid FNN	99.66	99.32	99.49

Figure.4: Results of Precision, recall and F- measure

F- Measure

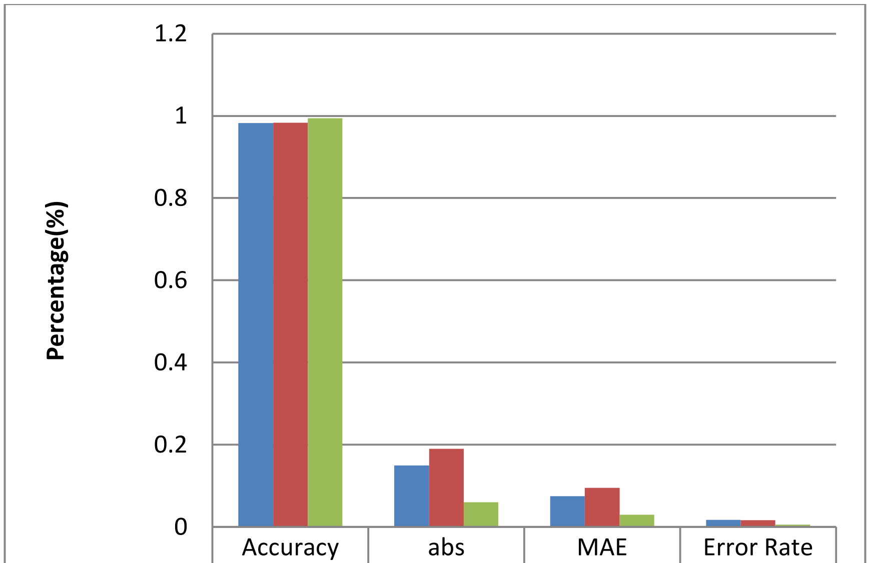
F – Measure or F – score is the mean of precision and recall. The product of precision and recall is divided by the sum of precision and recall to arrive at the F – Measure (Figure. 4). It is calculated by

$$\text{F – Measure} = \frac{\text{2.Precision.Recall}}{\text{Precision+Recall}}$$

Accuracy

The weighted percentage of action in frames is appropriately categorized by the accurateness and Figure.5 shows the comparison of the accuracy percentage of ISVM and Hybrid FNN. Hence,

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} * 100$$



	Accuracy	abs	MAE	Error Rate
ISVM	0.9827	0.15	0.075	0.0173
FNN	0.9836	0.19	0.095	0.0164
Hybrid FNN	0.9945	0.06	0.03	0.0055

Figure.5: Results of Accuracy and Error Rates

Error rates

The error rate, Absolute error (abs) and Mean Absolute Error, also known as MAE are the mostcritical metrics in the measurements of a model's accuracy. Though there are many ways to calculate the error rates; computing and summarising the above factors remains critical in gauging the machine learning model's quality.

Figure.5 shows the comparison of the error rate percentages of ISVM and Hybrid FNN.

i) Error rate = 1- Accuracy

ii)*abs* = True value – Actual value

iii) MAE = $\frac{1}{n}\sum_{i=1}^{n} \text{sum}(abs)$ (n = no. of training sets)

ONTOSkDS

The primary objective of this work was to propose an ontology using RDF/OWL and SWRL with DROOLS inference engine, for assessing the skin disorder of the patients effectively and efficiently. In this section, we investigated and showed the structure of ONTOSkDS and the results are depicted. Figure.6 is the output of NN using RDF and Figure.7 is the final structure (Proposed one which is the outcome of using swrl and sqwrl). Figure.8 (a) shows the classified rules generated using SWRL and Figure 8(b) shows the query results of each class in SQWRL.

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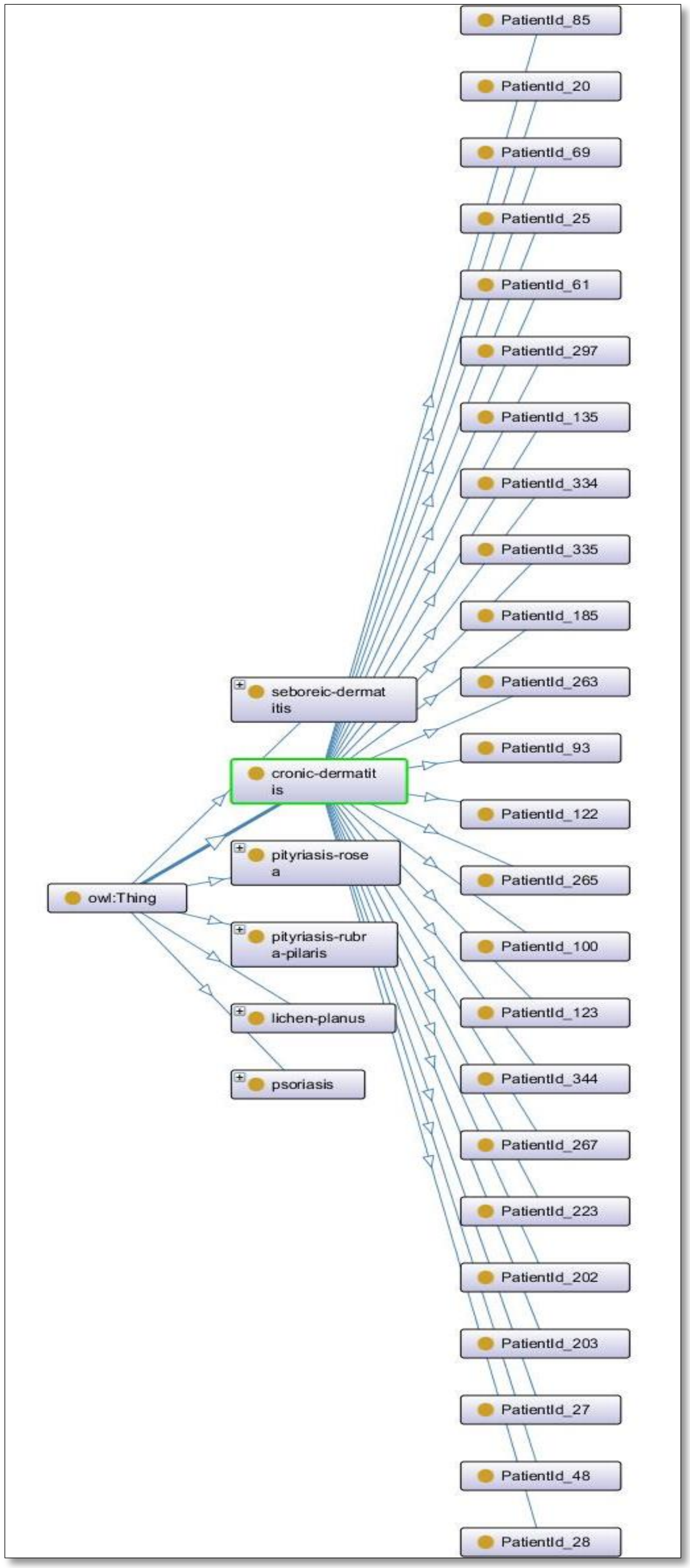

Figure 6: Output of Fuzzy- NN using RDF

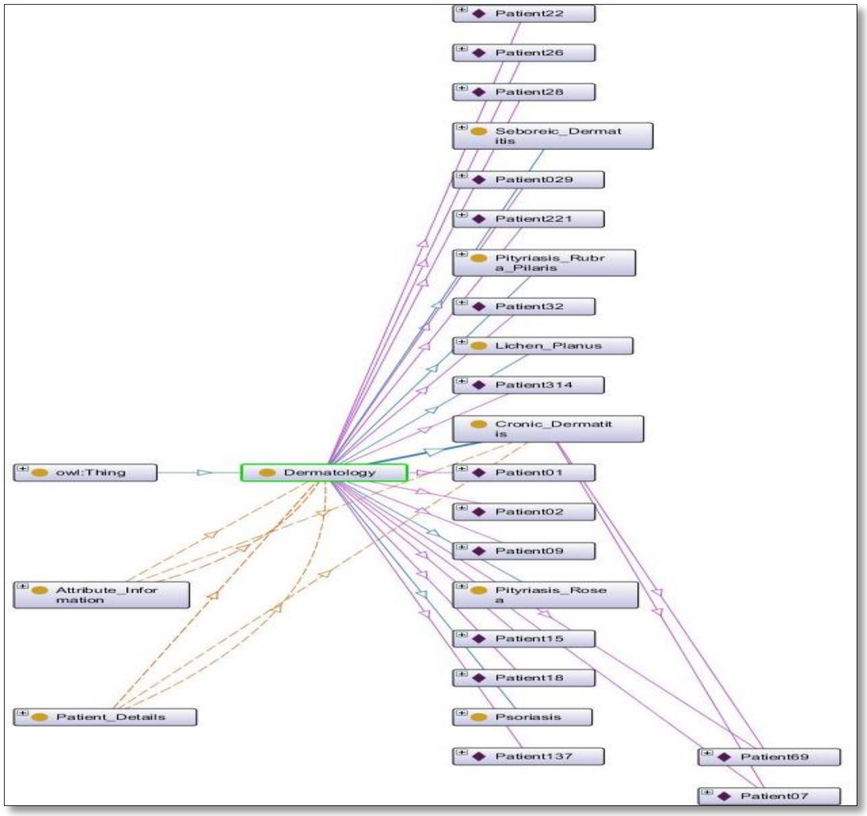

Figure.7: Relational Structure (Proposed one)

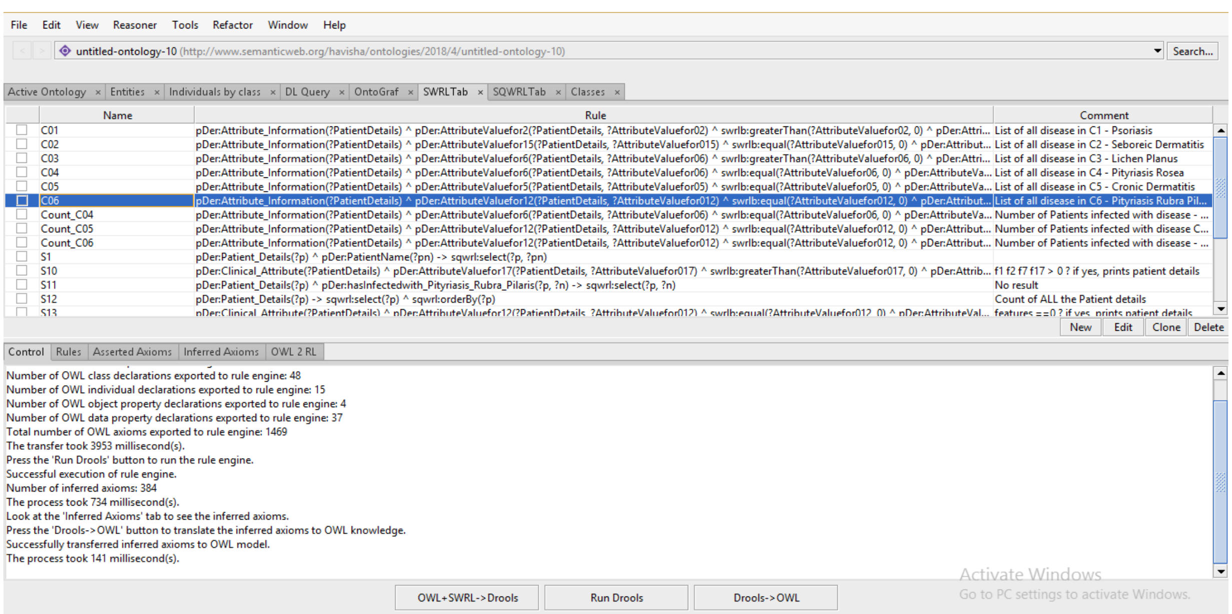

Figure 8(a): SWRL (Classified Rules)

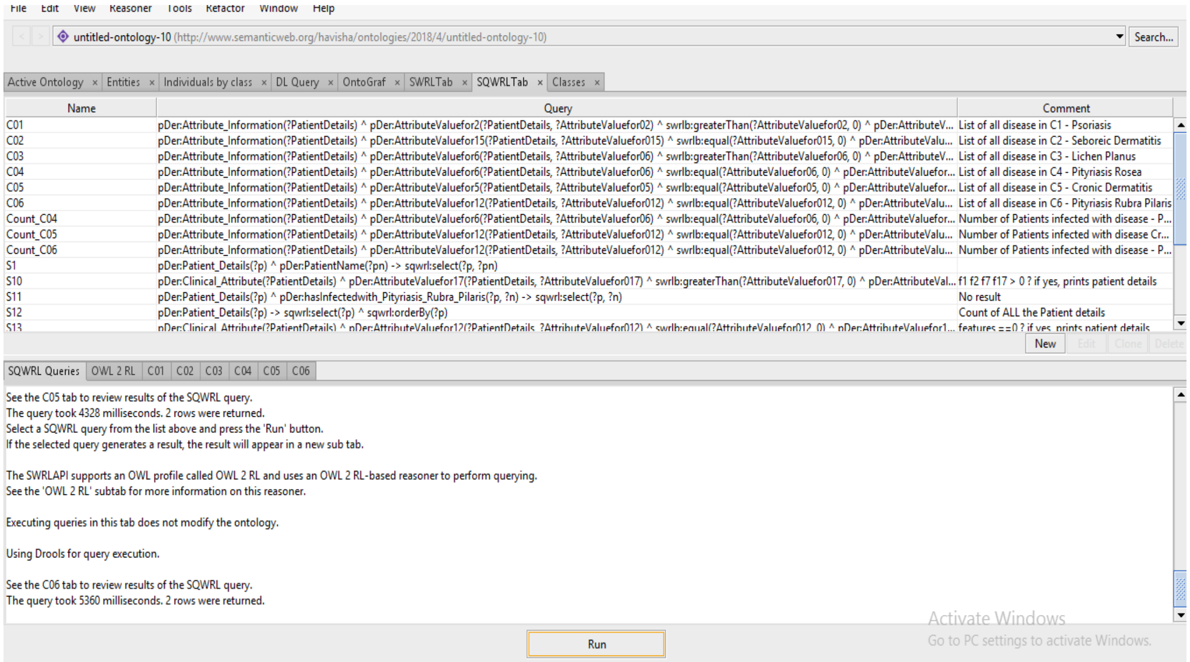

Figure 8 (b): SQWRL (to review results)

CONCLUSION

Dataset is pre-processed and trained with the help of Improved SVM. The resultant is then fuzzified to create Fuzzy rules which are then passed to Neural Networks where weights are assigned and the new rule set is defined. The obtained accuracy of the Hybrid FNN is 99.45% and this is greater than ISVM and FNN. This ruleset based on Hybrid FNN is then given to SWRL for creating a query for the corresponding classes which are predefined. The query is then passed to SQWRL for processing where the final structure is obtained indicating the clear picture of the patients with all related details associated with them. DROOLS inference engine helps in combining SWRL and ONTOSkDS to compare each structure that is obtained. The result gives the optimised structure proving the best of the model developed to CDSS which is used to give the best relational structure to decide on a time.

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