International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-5, Issue-11 E-ISSN: 2347-2693

Hybrid Legal Intelligent System Using Fuzzy and Neural Networks

S. Sridevi[1], P. Venkata Subba Reddy[2*]

[1]Computer Science and Engineering, Sri Venkateswara College of Engineering, Tirupati, India
[2]Computer Science and Engineering, Sri Venkateswara College of Engineering, Tirupati, India

[*]*Corresponding Author: pvsrpoli@hotmail.com*

Available online at: www.ijcseonline.org

Received: 26/Aug/2017, Revised: 09/Sep/2017, Accepted: 23/Sep/2017, Published: 30/Nov/2017

Abstract— In this paper, we describe the implementation of Hybrid Intelligence system for Indian legal domain by using neural network and fuzzy technique. The objective of this research is to develop a legal expert system for auto-insurance, a domain within the Indian legal system. We have proposed legal reasoning system which basically integrates rule based and case based reasoning in a structured manner for critical task units in auto-insurance domain. The end user of the system can be the insurer as well as lawyer in order to take any legal actions. The system mainly handles three main functional blocks of auto-insurance claim processing: i) validation of rules and regulations of motor vehicle act, ii) verification of the 'extent of damage' attribute, and iii) analysing history legal cases for reference. The scope of this hybrid system is limited to validation and verification of auto-insurance claim processing pertaining to Indian legal system. All these functional blocks play important role in providing logical solution for claim compensation.

Keywords— Fuzzy Legal Expert System, Fuzzy Case Based Reasoning System, Hybrid Expert System, Hybrid Legal Intelligent System, Legal Intelligent System, Neural Network.

I. INTRODUCTION

Developing a legal expert system involves, first and foremost, legal analysis. A system's designer must have a fair understanding of corresponding domain laws, rules, regulations and cases, and how they relate to each other. Our system is basically a combination of legal analysis and legal retrieval, to provide comprehensive solution for auto-insurance claim processing. Our hybrid system is built by integrating rule based and case based reasoning with fuzzy logic and neural network technology. There are three collaborating modules in the system. The first one is the rule based reasoning (RBR) module, which handles the legal analysis part, basically a set of rules named as Indian Motor vehicle act. The Motor Vehicles Act, 1988 is an act which regulates all aspects of road transport vehicles. The second module deals with functional part of legal retrieval through case based reasoning (CBR) using fuzzy logic. CBR part assists lawyers to look into the relevant cases when considering a particular claim dispute. Claim assessment depends on situation data which is usually uncertain in nature. Handling uncertainty information during auto-insurance claim processing directly relates to weight of information, and usually varies with expertise of domain expert. Neural Networks is a suitable approach to deal with this type of problem. Subsequent sections describe design and flow chart of how these three modules function and how they are connected to each other. The scope of the system is limited to finding few categories of suspicious claims which needs to be further investigated to identify as soft fraud. The Neural Network (NN) module takes the 'severity of impact' parameter into account, and recommends a standardised possible 'extent of damage' parameter.

The idea behind the development of this hybrid system is towards achieving the goal of speedy settlement and better control over auto-insurance claim. This system can be used by claim processing official (insurer) as a standard for comparison while scrutinising the insurance survey report. So this system, helps in identifying any major deviations, not within tolerance limit should prompt the claims processing official to take further action.

II. LITERATURE REVIEW

This topic covers an outline of some successful legal expert systems (LES) that have previously been implemented. The LES can be broadly classified into three main categories: rule based reasoning, case-based reasoning and hybrid systems (using a combination of RBR and CBR). Some of the successful Legal Expert Systems listed in category wise are:

CBR Legal Expert System:

FINDER**:** This system was created by Tyree, Greenleaf, and Mowbray and based on law of trover. The law of trove is a common law based on the rights of finders of lost chattels. FINDER operates using the nearest neighbour analysis. HYPO**:** Deals with trade secrets law and is well documented CBR system. Hypo was developed by Kevin Ashley and Edwina Rissland at the University of Massachusetts. OPINE[2]**:** A generic case-based reasoner for use in legal domains. OPINE has a single function working methodology that results in likely case outcome in particular legal context. HIROTA [1]: A fuzzy Case based Reasoning system for legal inference. JUDGE [3]: system developed for the criminal law domain to model the sentencing of criminals done by real-life judges by matching past cases to current case.

RBR Legal Expert System:

JUDITH [4]: The methodology behind Popp and Schlink's JUDITH system is similar to those of the MYCIN system (Rule-based medical expert system). TAXMAN [5]: Is rule-based reasoner deals with taxation of organizations. The knowledge contained in this system includes corporate tax cases and tax laws. SplitUp [6]: The design methodology behind this system includes neural network theory apart from if-then rules. The main functionality of this system is to make predictions about the distributions of marital property following divorce in Australia.

Hybrid Legal Expert System:

GREBE (GeneratoR of Exemplar-Based Explanations) system deals with Texas workers compensation law. In this system RBR and CBR run concurrently. The Rule Base includes statutory, common law and commonsense laws. PROLEXS [van Opdorp et al.1991] is a dutch system deals with the landlord-tenant law. Rule based reasoning is used for legislation knowledge and the case based reasoning is used for case law knowledge. IKBALS[8] adapts a distributed AI approach and primarily focuses in the area of credit law. CBR and RBR operate in a parallel nature and are totally independent agents. IKBALSII[8] deals with accident compensation domain and is combination of RBR and CBR in order to determine if an injured employee is eligible to compensation only when worker falls under statutory rules. SHYSTER-MYCIN [9] is a legal expert system integrating SHYSTER (a legal expert system) and MYCIN (a medical expert system). The design of the system was mainly concentrated on the MYCIN (rule-based) part of the system and was modified to support requirements of the system. The SHYSTER (Case based) part was invoked on demand and was not modified. Gun Ho Lee[10] proposed integrated approach that is combination of RBR and CBR for bank auditing system. The knowledge base of RBR comprises of application specific domain rules and regulations. The CBR executes similarity-based matching to find the most similar case to the new problem in form of case. The hybrid system suggested by Robert T.H.Chi and Melody Y.Kiang[11] includes both a case base which stores past cases and an explanation mechanism which uses domain theory to generalize the old cases to cover a wide range of problems.

Legal Reasoning using fuzzy and neural networks:

Fuzzy logic and neural networks are extensively used in development of legal expert system and these technologies have great future in automation of legal system. In this paper [12], fuzzy theory is applied for case representation and Case Base Reasoning (CBR) for legal inference. According to [13], vague legal concepts can be represented using fuzzy logic. Jong-Uk Choi[14], systematically designed legal expert system where uncertainty issue is handled using fuzzy database. Ambiguity and vagueness of expression can be solved by fuzzy inference. In this paper [14], neural network is applied to auto insurance domain to fine tune output and for handling uncertainty problem. And also author explains how neural networks handle changing situations in processing of auto insurance claim processing.

III. HYBRID INTELLIGENT SYSTEMS APPROACH

The components of hybrid intelligent system are integrated using mainly three strategies: loosely coupled, tightly coupled, and, fully integrated. In loose coupling model, the integrated components are operated in a independent manner that is each of which can solve the problem independently of the other. The communication between the components is achieved through data files. RBR and CBR can be combined in three flavours: RBR first, CBR first, or some interleaving of the two. The RBR-first strategy is suitable, when the rules are reasonably efficient to begin with. Our proposed system is built upon loosed coupled model and the RBR-first strategy.
The hybrid approach has been found appropriate to enhance the strengths of individual working technique and overcome the weakness, there by addressing more critical problems. The real advantage of the hybrid approach is, the entire system will maintain the individual strengths of respective component technologies.

IV. AUTOMATION OF LEGAL REASONING WITH HYBRID INTELLIGENT SYSTEM

This paper describes a prototype legal hybrid intelligent system which attempts to validate statute rules through deductive reasoning or rule based reasoning in the area of auto-insurance claim processing. Precedent cases are referred through analogical reasoning or case based reasoning. The system allows lawyers to retrieve and analyze sources of laws namely Motor Vehicle Act, 2001 and associated cases so as to successfully develop a reasonable argument for their client in court. Moreover, this system identifies any variations in report prepared by the auto-insurance surveyor. These deviations are determined using neural network approach.
The system is explained using use case diagram, architecture diagram and flow chart. The basic functional flow of motor-insurance claim process based on IRDA (Insurance regulatory and development authority of India) is as follows: In motor, there can be two types of claims i.e., own damage (vehicular damage) and third-party (person injury and property) claims. The interactions between the insurer, insured and surveyor is better illustrated using the Use Case diagram (Fig 1). The surveyor is a professional who assess the loss or damage and serve as a link between the insurer and the insured. The scope of this system deals with own damage (OD) claims only. The surveyor prepares surveyor report,

contains information like: cause and nature of accident, total repair cost etc, which in turn handed over to insurer for further processing. The use case 'Basic validation' performs preliminary motor regulations, core functional part is handled by use case 'Extent of damage verification'.

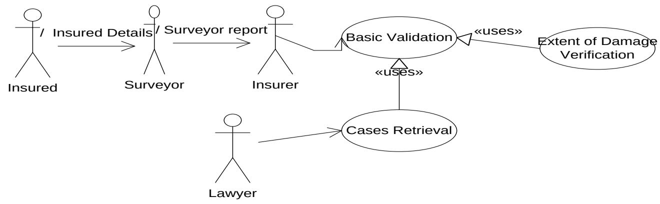

Fig 1: Use Case Diagram of Legal Reasoning

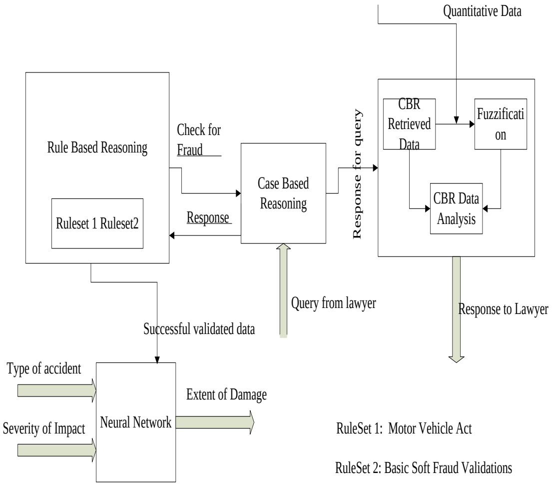

Fig 2: Block diagram of Hybrid Legal Expert System

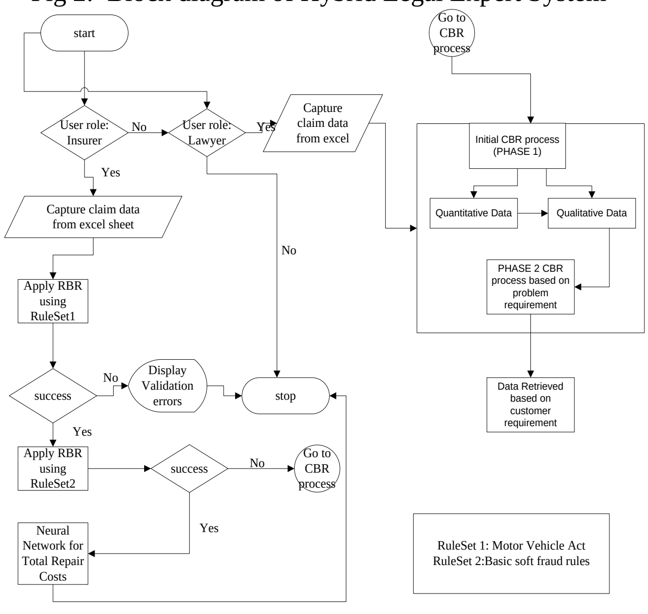

Fig 3: Process flow chart of Hybrid Legal Expert System

The Figure 2, illustrates functional modules involved in the system and the way modules interact. There are three modules: Rule based reasoning (RBR), Case based reasoning(CBR) and Neural network (NN) computation. RBR module executes two rule sets, first one for preliminary validations and second one for detecting very basic soft. The control flows to other modules based on condition triggers. These condition triggers are explained in Fig 3. The Case based reasoning works in dual mode. While user enters system as insurer, CBR module checks for soft fraud by searching data base for any precedent/history record. In different scenario, where user enters as lawyer with different data format supporting third party claim, the system comes with set of solutions based on user requirements. Neural network module recommends 'extent of damage' parameter only when all basic validations are successfully passed. The figure 3 depicts flow chart of system as summarized as below:

Step a) System end user can be insurer or lawyer. If it is insurer, go to step 2 otherwise if it is lawyer, go to step 3. In both cases claim data is read from excel sheet.

Step b): User is insurer: An insurance claim has been received at this point. The details relating to the event(accident etc.,) have been provided in the surveyor report. The report contains information like details of insurer party, accident description, claimed amount, extent of damage as assessed by surveyor. The result base RBR module is invoked, and is provided the information listed about as input. The module checks the validity of the policy, validity of the licence etc. by firing 'Ruleset1'(motor vehicle act rules and regulations). If all rules are successfully validated then it implies that claim is a valid claim. For invalid claim, the system displays appropriate errors and stop execution. For valid claim, the system applies 'Ruleset2'. 'Ruleset2' mainly contains very basic soft fraud rules using which we can suspect claim and sent to CBR module for any past/history entry. The control then flows to neural network routine which on basis of input provided recommends a 'extent of damage' value which impacts amount offered by insurer.

Step c): User Lawyer: The CBR process is initiated with third-party claim data. Detailed explanation steps of CBR process with algorithm is elaborated in section (Fuzzy Case Based Reasoning system for legal inference). Data to be loaded in the CBR must support Motor Accident Claims Tribunal (MACT). The MACT Tribunal deals with claims relating to property and injury cases resulting from Motor Accidents.

A. *LEGAL RULE BASE INFERENCE*

The rule based reasoning module implements two types of rule sets as mentioned in flow chart process. A few of the important variables of each claim are: vehicle age, vehicle registered number, unladen weight, registered laden weight, claim amount, fitness certificate date, motor driving licence number, vehicle class, nature of accident and vehicle permit type etc. The system being proposed validates the motor vehicle act rules and regulations using these variables. A few of the rules from ‘RuleSet1’ are listed below:

policy1: if class_ of_ vehicle equals ‘LightMotorVehicle’ AND unladen weight <=7500kgs then policy_valid = true

policy2: if fitness_certificate_date > claim date then policy_valid = true

RBR module in this system deals with Own Damage (OD) claims only.

A few of the rules from ‘RuleSet2’ are listed below:

Some basic and preliminary checks for identifying suspicious claims are:

check1: if (claim_amount is greater than *Threshold*) then claim history is checked for frequency and type of claim in case base.

check2: if (claim_amount is greater than *Threshold* and vehicle_age > 8 yrs) then suspect_fraud = true.

B. *FUZZY CASE BASED REASONING SYSTEM FOR LEGAL INFERENCE:*

In legal case-based reasoning (CBR), fuzziness exists in problems e.g., representation of precedent cases, their retrieval and similarity measures. Fuzzy CBR can be termed as value added to conventional CBR.

The studied CBR system works in two steps which are filtering and selection:

1. In case filtering step based on some criteria, potentially interesting cases are identified.
2. In selection step, nearest cases are selected based on fuzzy similarity measure.

In this hybrid integrated system, each case is represented by a conceptual entity called frame.

Frame mainly constitute of three types of slots and value associated with each of the slot, namely common slots, critical slots and decision slot.

Fuzzy CBR process mainly consists of flow like this: when a problem request is encountered, key features of the problem are identified. These features are then used to retrieve most promising cases from the case base. These promising cases are further analysed to select cases based on problem requirement by making use of suitable similarity measure. Before analysing, required quantitative attribute is fuzzified, following below procedure:

1. Quantitative attributes are identified from filtered case;
2. For each quantitative attribute, proper classes are determined based on problem specification;
3. The membership function of each class and its associated apha-cut are determined.

Membership functions for Quantitative attribute ‘Driver Age’:

Young:A(x) = 1 when $x<=20$
= (35-x)/15 when $20<x<35$
= 0 when $x>=35$

Middle-aged:A(x) = 0
When either $x<=20$ or $>=60$
= (x-20)/15 when $20<x<35$
= (60-x)/15 when $45<x<60$
= 1 when $35<=x<=45$

Old:A(x) = 0 when $x<=45$
= (x-45)/15 when $45<x<60$
= 1 when $x>=60$

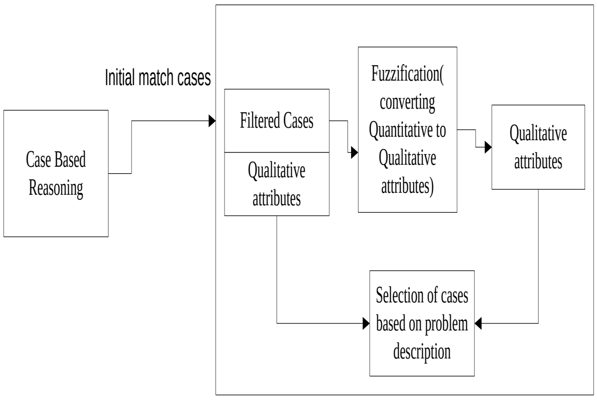

Fig 3: Fuzzy CBR process diagram

Table 1

Figure 1. **Po licy**	Figure 2. **Driver age**	Figure 3. **Subcategory**	Figure 4. **ehicle class**	Figure 5. **Nature of accident**	Figure 6. **Category**	Figure 7. **Fuzzified** Figure 8. **Driver Age**
Figure 9. A	Figure 10. 29	Figure 11. Fake_licence	Figure 12. MV	Figure 13. minor	Figure 14. licence	Figure 15. 0.4/y,0.6/m,0/old
Figure 16. B	Figure 17. 30	Figure 18. Invalid_licence	Figure 19. MV	Figure 20. minor	Figure 21. licence	Figure 22. 0.3/y,0.6/m,0/old
Figure 23. C	Figure 24. 20	Figure 25. expired_licence	Figure 26. MV	Figure 27. minor	Figure 28. licence	Figure 29. 1/y,0/m,0/old
Figure 30. D	Figure 31. 40	Figure 32. Fake_licence	Figure 33. MV	Figure 34. major	Figure 35. licence	Figure 36. 0/y,1/m,0/old
Figure 37. E	Figure 38. 50 Figure 39.	Figure 40. drunk_driving	Figure 41. MV	Figure 42. critical	Figure 43. negligence driving	Figure 44. 0/y,0.6/m,0.3/old

To simplify representation, a case consisting of driver age, vehicle class, problem_subcategory is represented as a three-tuple following the name of the case, that is casename(driver_age,problemsubcatgory,vehicleclass).Hence Ashok(30,fake_licence,LMV) means person called Ashok whose age is 30 yrs, holding fake licence and vehicle class type is light motor vehicle. For Ashok(30, fake_licence, LMV), the fuzzifier converts age value 30 into membership grades of the respective classes: 0.3 for young, 0.6 for middle-aged, 0 for old which can be

represented as (young/0.3, middle-aged/0.6, old/0). If alpha-cuts are set at 0.5, then Ashok can be classified as middle-aged person.
Given the cases in Table 1, suppose we want to assess the 'nature of accident' of person whose age is 40 yrs and problem_subcategory is fake_licence. Based on the membership function defined previously, the age 40 yrs can be converted to middle_aged/1, and the case becomes Ashok(X, middle_aged/1, fake_licence), where X stands for an unknown value. We can easily find that policies A and D match the known attributes of the new case and can be used as bases for assessing the nature of accident of person Ashok. Fuzzy retrieval often results in a set of candidate cases for reasoning. The issue following fuzzy retrieval is to find the most similar case among candidates. In our example, case A indicates that the 'nature of accident' is minor, whereas case D indicates that the 'nature of accident' is major. There are several ways of finding the most similar case.

Algorithm for suitable case retrieval based on problem requirement using CBR approach:
For case representation, first identify key features. These features can be termed as slots and identify common slots, critical slots and decision slots. This constitutes a case frame.

1. Load predefined cases into case base.
2. Retrieval step consists of two stages

First stage:
Cases are retrieved using qualitative attribute as key and saved in data structure which usually stores items in form of key and value pair for better retrieval in second phase and enables grouping cases according to 'subcategory'.
This qualitative attribute is configurable, changes according to business need.
Basically data structure stores key as critical slot attribute and remaining slot attributes in case frame as value. This stage results in retrieving potential relevant, promising and interesting cases from case base.

Second stage:
Cases are matched based on problem description in order to select nearest cases.

a. Retrieve cases from data structure obtained from first stage as per requirement.
b. Convert Quantitative variables into fuzzy variables and determine its associated alpha-cut.
c. The similarity function between the case c = { $f_1^c, f_2^c, \ldots$} and target t = { $f_1^t, f_2^t, \ldots$} is given by the weighted sum

$$\sum_{i=1}^{n} w_i . SIM(f_i^t, f_i^c) / \sum_{i=1}^{n} w_i$$

Where w_i is the weight for the ith feature
Where $SIM(f_i^t, f_i^c) = \max\min(\mu_t(i), \mu_c(i))$,
where $\mu_t(i), \mu_c(i)$ are membership functions.

d. Apply fuzzy similarity measure between the attributes to select nearest case
e. The similarity degrees of each attribute are aggregated, taken into account their importance weight, using weighted average method.

3. Label each case appropriately using similarity threshold and select case based on problem requirement.
4. Based on problem specification, some of extended Retrieval flexibility options are
   i. Relation based between subcategory and nature of accident
   ii. Count the number of cases showing a particular result, generally used for classification problem
   iii. Pattern based AND,OR operations between attributes.
   iv. Fuzzy retrieval with modifiers ex: very, somewhat etc.

C. Handling Uncertainty problem using Neural Network (NN):
There is lot of uncertainty issues involved in auto-insurance claim process like incomplete information and unreliability of information. The property damage information depends on many factors like situation of accidents, behaviour of the driver, causes of the accident and vehicle in the accident, and humans in accidents. Weights of causes of property damage information are varied by expertise of auto-insurance experts. Neural Network is the suitable approach to handle this type of problem. The property damage in turn relates to "total repairs cost". The amount of claim payable depends on mainly "Total repairs cost".
Calculating 'total repair cost' is most critical portion of standardisation of claim assessment technique. This parameter plays important role in loss minimisation process. The factor 'total repair cost' which itself is influenced by many other items, as indicated below

a. The extent of Damage
b. The kind of workshop where the damaged vehicle is to be repaired.
c. Jobs to be carried out.

The scope of this paper is limited to assessing the "extent of damage" parameter through neural network. Extent of damage depends on

a. Nature of accident
b. Severity of Impact

These two factors in turn depend upon certain other factors as shown below:

A. Nature of accident (Types):
   1. Collision 2. Hit against fixed objects (tree like objects. Culvert/milestone like objects). 3. Capsizing on side 4. Roll-over
B. Severity of impact depends on
   1. Age of vehicle 2. Vehicle with load/without load 3. Speed at which the vehicle was moving.

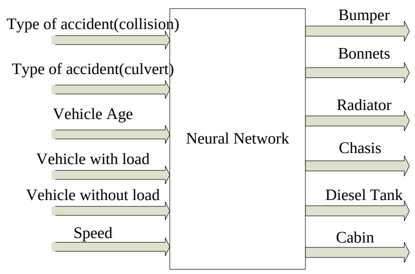

Fig 4: Neural Network for assessing damages

Final outcome of the Neural Network "extent of damage" parameter derives from many attributes bumper, bonnets, radiator, chasis, diesel tank and cabin. "Extent of damage" is one of important factor which can be used for comparison with the information contained in a survey report. When there is significant variation, the reason has to be analysed and clarification obtained if necessary the assessment can be revised.

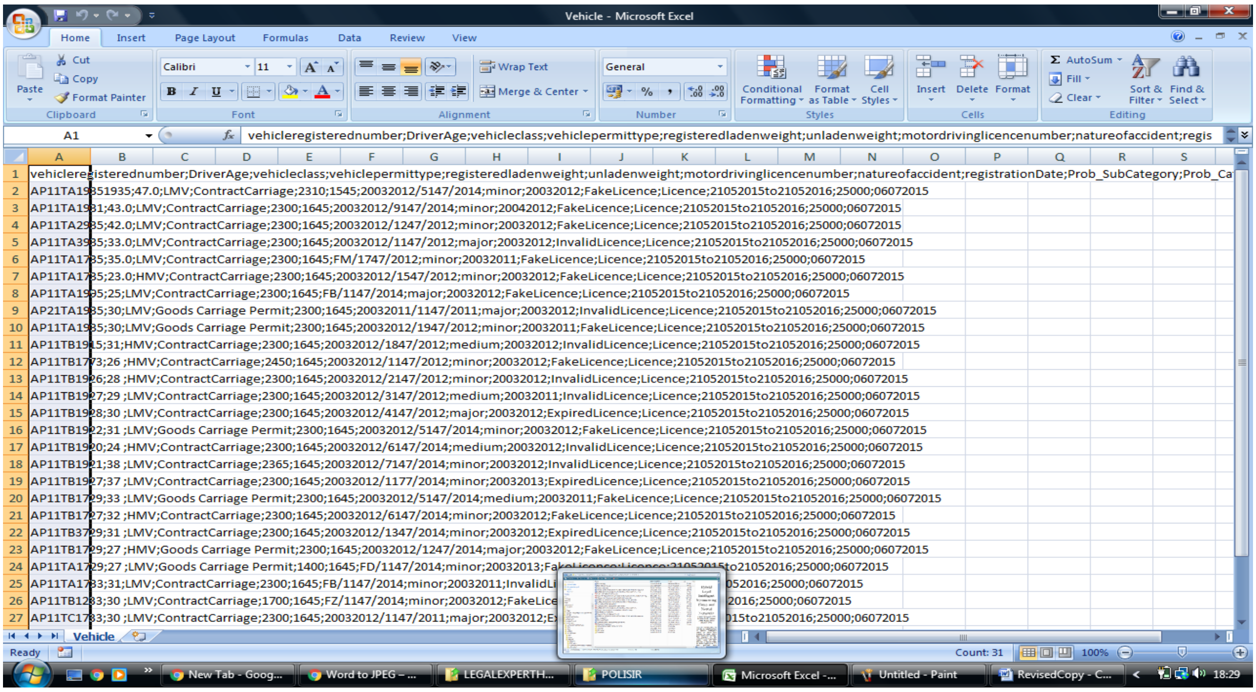

Fig 5: Auto-insurance excel data imported into CBR knowledge base

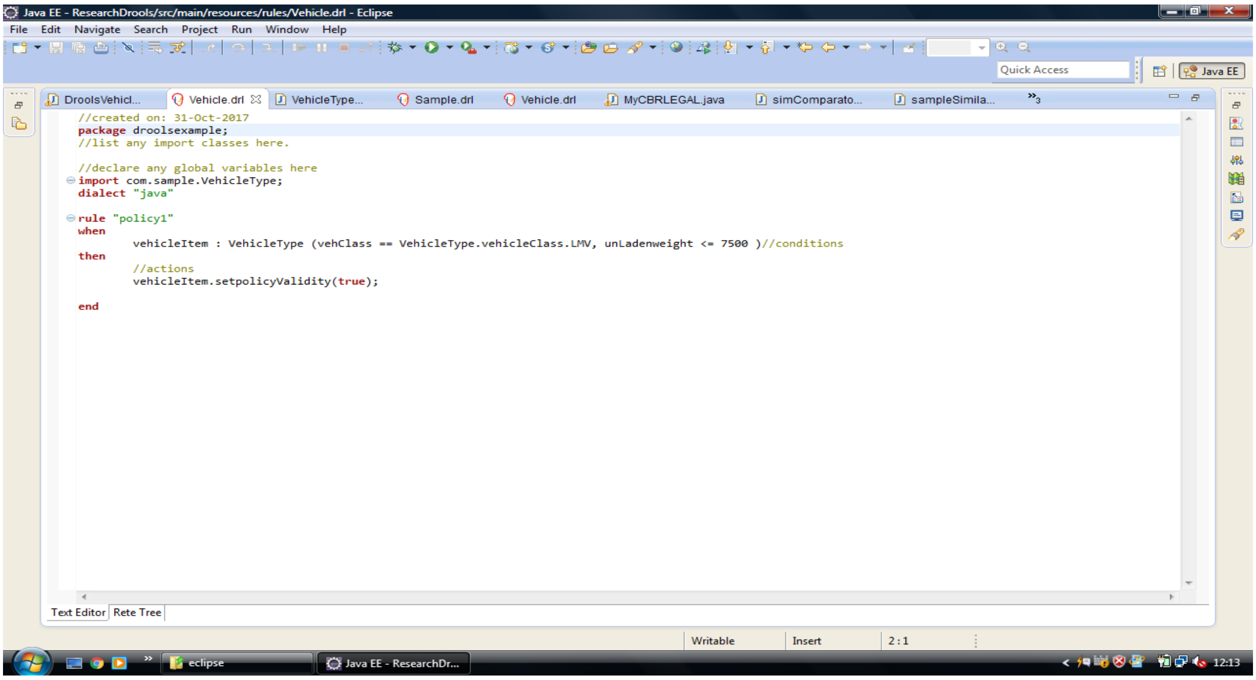

Fig 6: Drools Rule Language (DRL) for policy1 rule

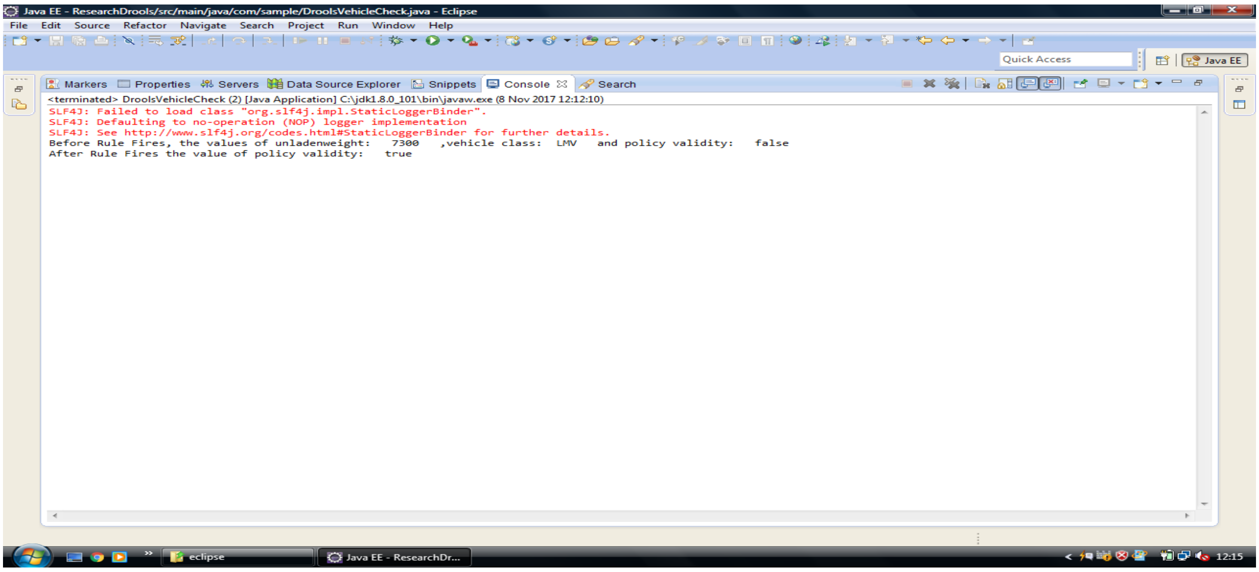

Fig 7: Policy 1 output

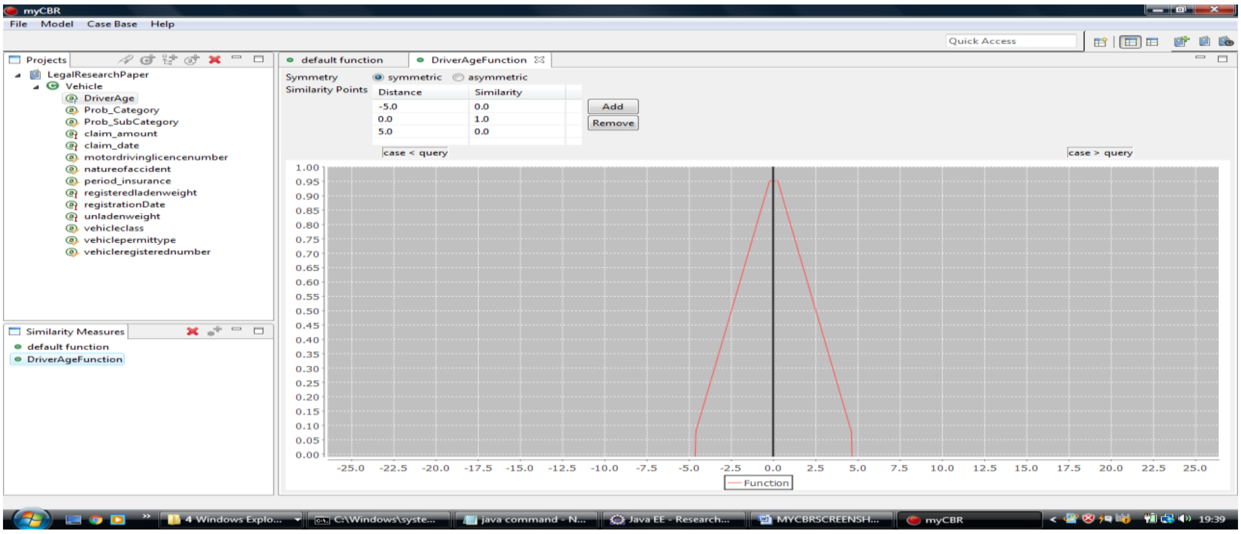

Fig 8: DriverAge parameter customized similarity

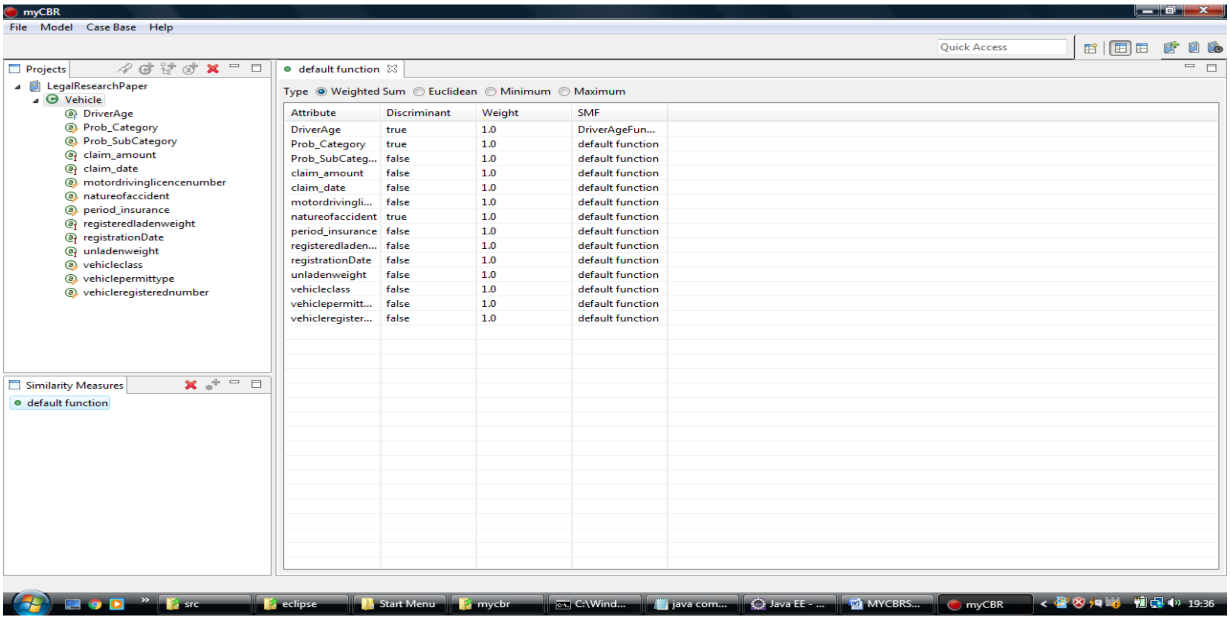

Fig 9 (Below): Query with discriminator values

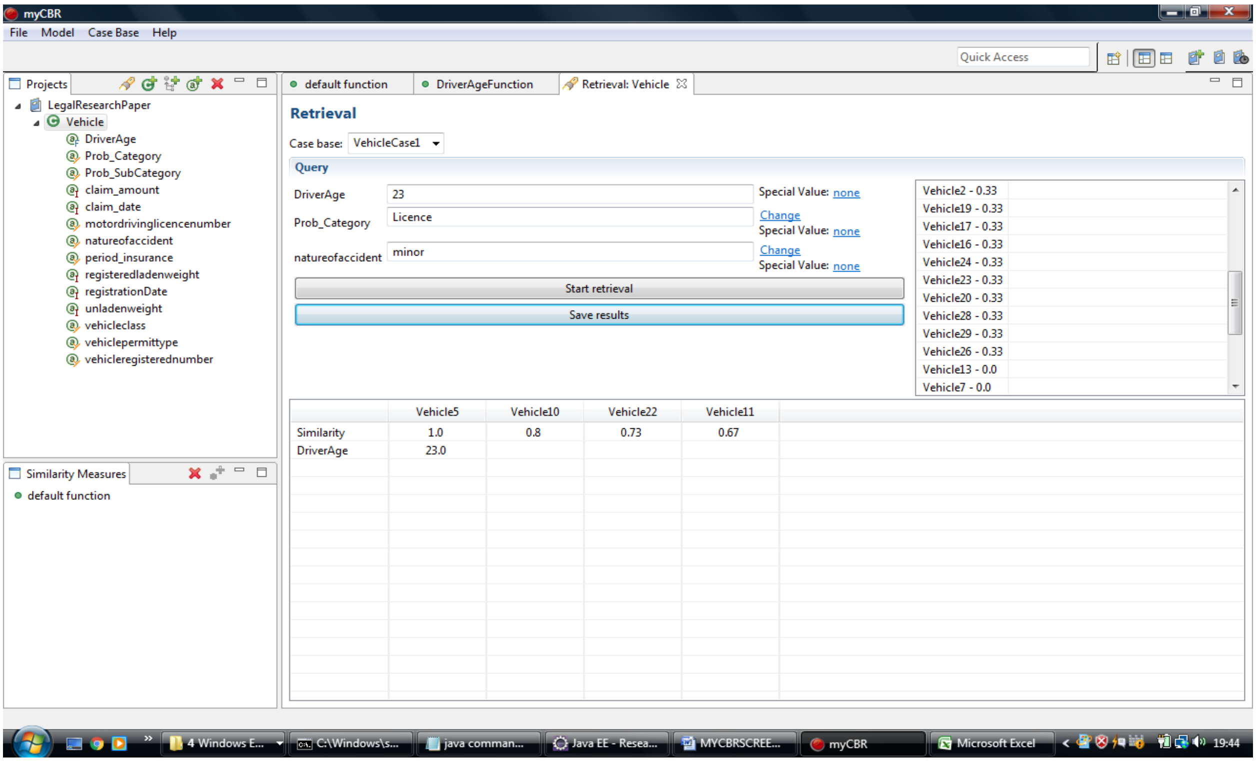

FIG 10(BELOW): INPUT QUERY WITH PARAMETER VALUES

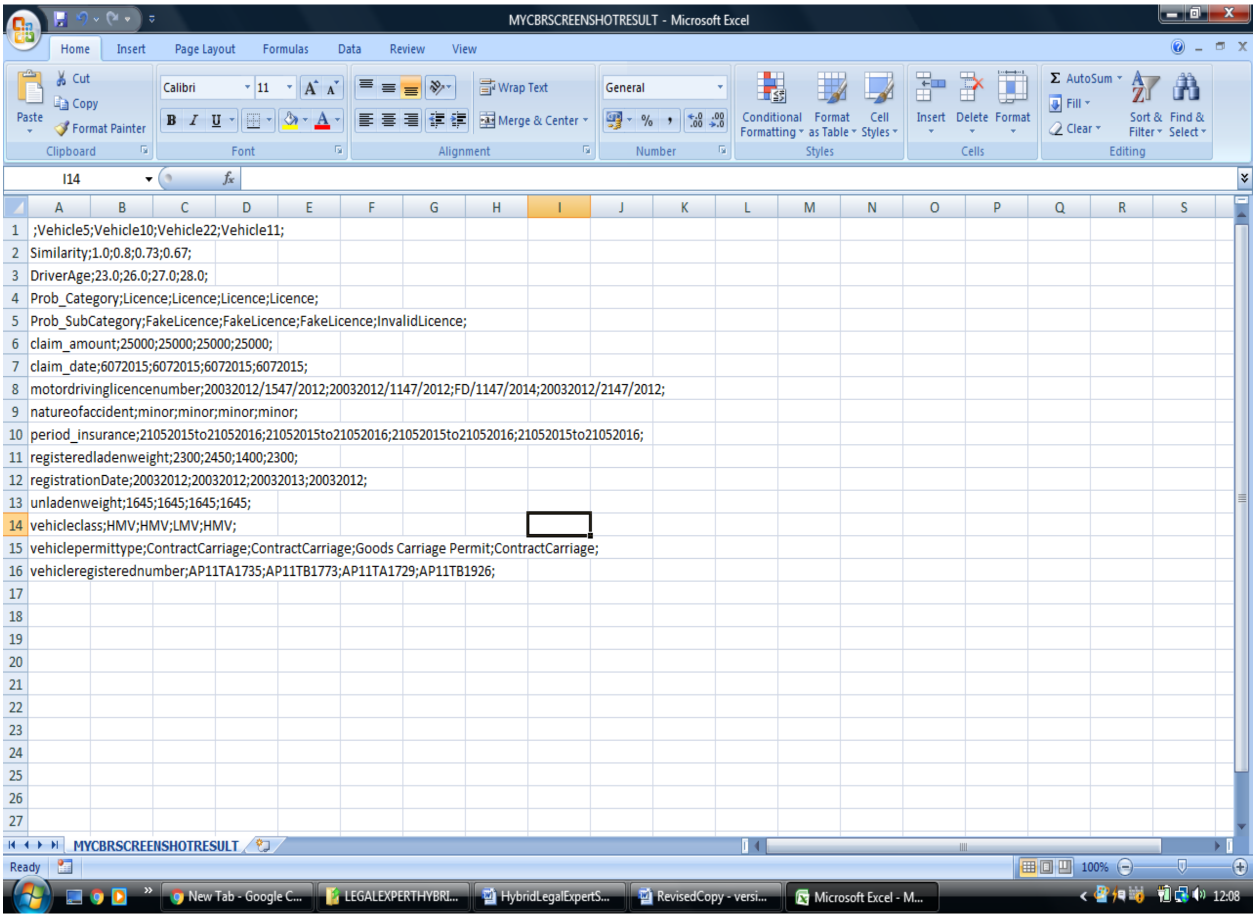

Fig 11:CBR output in excel format

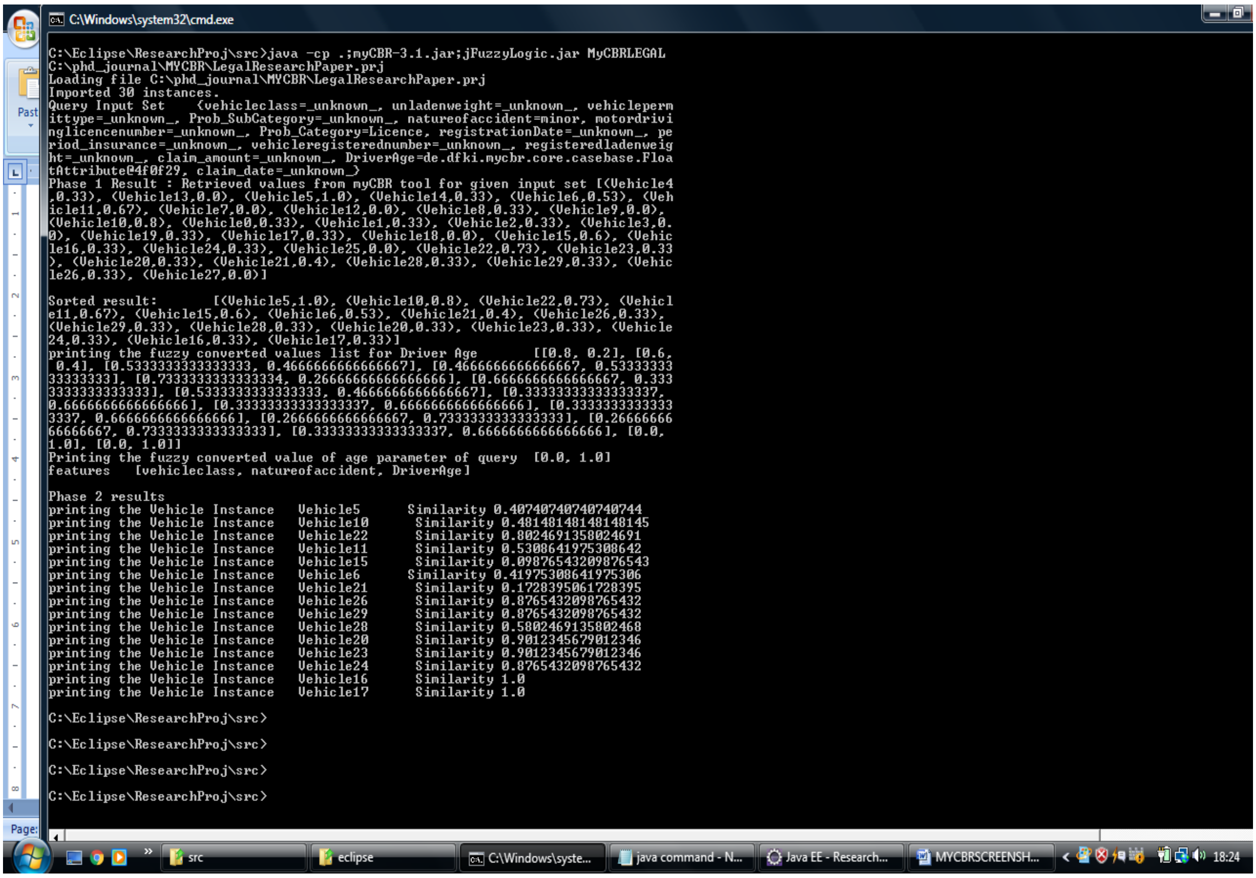

Fig 12(Below): Final CBR output with similarity values

V. PROTOTYPE DEVELOPMENT OF HYBRID SYSTEM

The first reasoning module, RBR is implemented using Drools**.** Drools is a business rule management system with a forward-chaining and backward-chaining inference based rules engine, allowing evaluation of business rules. A rule engine is also a fundamental building block to create an expert system which, in artificial intelligence, is a computer system that emulates the decision-making ability of a human expert. The rule 'policy1' of RuleSet1 as prescribed in section (Legal Rule Base Inference) is implemented using this tool drools and screenshots of DRL file and output is depicted in Fig 6 and Fig 7. As per algorithm defined in section (Fuzzy Case Based Reasoning system for legal inference), the implementation is done using tool MYCBR and results are outlined in Figures 8 to 12. As per Hybrid System flow chart in Fig 3, if the user login to a system as 'insurer', first and foremost there are set of policy rules are executed. Since its prototype, for demonstration purpose, screenshot with one policy rule (policy 1 rule of RuleSet1 as described in section: Fuzzy Case Based Reasoning system for legal inference) has been implemented using drools tool as shown in Fig 6 (DRL file) and its output in Fig 7. If there is any soft fraud, then request hits the CBR module. The Figures 8 to 12 are sample screen shots of CBR input query parameters and its corresponding output. The format of CBR input query parameters is based on 'insurer' problem specification

.

CONCLUSION

This paper focused mainly on domain analysis and study of components of Legal expert system for motor insurance claims assessment. This study has shown how AI technologies mainly fuzzy, expert system and neural networks can be connected making hybrid expert system framework. This system tries to automate some of the functionalities of the motor insurance claim assessment. This tool can speed up the manual process and most advantageous to insurer and lawyers.

Scope of paper is limited to preliminary motor vehicle checks pertaining to Indian legal domain and assessing crucial parameter 'extent of damage'. This model tries to reuse case base by performing some very basic soft fraud checks. By applying these fraud checks, we can only suspect claim. Identifying suspected claims as real soft fraud or not is not within scope of this paper. Future work is, author is in process of prototype development of neural network module of this hybrid model.

REFERENCES

[1] Kaoru Hirota, MingQiangXu, Yasufumi Takama and Hajime Yoshino, "Implementation of Fuzzy Legal Expert System FLES".

[2] William M.Bain,"Judge: A Case-based Reasoning System ".

[3] Kevin D Ashley,"Case-Based Models of Legal Reasoning in a Civil Law Context".
[4] Walter G. Popp and Bernhard Schlink," JUDITH, A COMPUTER PROGRAM TO ADVISE LAWYERS IN REASONING A CASE "
[5] L.Thorne McCarty, "Reflections on TAXMAN: An Experiment in Artificial Intelligence and legal reasoning"
[6] John Zeleznikow,"Split-up: a web-based legal decision support system that advises upon the distribution of marital property
[7] Rissland, E.L., Skalak, D.B.:"CABARET: Statutory Interpretation in a Hybrid Architecture. International Journal of Man-Machine Studies (IJMMS)"
[8] George Vossos, John Zeleznikow and Daniel Hunter, "The IKBALS project: Multi-modal reasoning in legal knowledge based systems by George Vossos, John Zeleznikow and Daniel Hunter".
[9] James Popple, Eric McCreath," SHYSTER-MYCIN: A Hybrid Legal Expert System by Thomas A.O'Callaghan".
[10] Robert T.H.Chi and Melody Y.Kiang, "An Integrated Approach of Rule-Based and Case-Based Reasoning for decision support".
[11] Piero P. Bonissone, Ramon Lopez de Mantaras, "Fuzzy Case-Based Reasoning Systems".
[12] Kaoru Hirota, MingQiangXu, Yasufumi Takama and Hajime Yoshino," Implementation of Fuzzy Legal Expert System FLES".
[13] Pero Subasic , JURGEN HOLLATZ," Analogy making in legal reasoning with neural networks and fuzzy logic".
[14] MINGQIANG XU , KAORU HIROTA and HAJIME YOSHINO, "A fuzzy theoretical approach to case-based representation and inference in CISG".
[15] Jim Prentzas, "Categorizing Approaches Combining Rule-Based and Case-Based Reasoning".
[16] Jurgen Hollatz, "Analogy making in legal reasoning with neural networks and fuzzy logic", *Artificial Intelligence and Law* 7: 289–301, 1999.
[17] Piero P. Bonissone, Ramon Lopez de Mantaras, F4.3 Fuzzy Case-Based Reasoning Systems
[18] Jang-Hee Yoo and Byoung-Ho Kang, "A Hybrid Approach to Auto-Insurance Claim Processing System"
[19] N B Bilgi, Dr. R V Kulkarni & Clive Spenser, "An Expert System using A Decision Logic Charting Approach for Indian Legal Domain With specific reference to Transfer of Property Act"
[20] Thomas Alexander O'Callaghan, A Hybrid Legal Expert System
[21] Mariana Maceiras Cabrera, Ernesto Ocampo Edye, " Integration of Rule Based Expert Systems and Case Based Reasoning in an Acute Bacterial Meningitis Clinical Decision Support System"
[22] Gun Ho Lee," Rule-based and case-based reasoning approach for internal audit of bank", Knowledge-Based Systems 21 (2008) 140–147
[23] BING CHIANG JENG AND TING-PENG LIANG, "Fuzzy Indexing and Retrieval in Case-Based Systems", Expert Systems with Applications, Vol. 8, No. 1, pp. 135-142, 1995
[24] J. Popple,"Legal expert systems: The inadequacy of a rule-based approach
[25] John Zeleznikow, Andrew Stranieri, "Using Machine Learning to construct legal knowledge based systems"
[26] Andrew Stranieri, John Zeleznikow, Mark Gawler, Bryn Lewis," A hybrid rule - neural approach for the automation of legal reasoning in the discretionary domain of family law in Australia".
[27] H. Prakken, A.J. Muntjewerff, A. Soeteman, Legal knowledge based systems JURIX 94 The Relation with Legal Theory"
[28] Hyung Lee-Kwang, Yoon-Seon Song and Keon-Myung Lee, similarity measure between fuzzy sets and between elements, Fuzzy Sets and Systems 62 (1994) 291-293
[29] Michael Aikenhead Follow, The Uses and Abuses of Neural Networks in Law, Santa Clara High Technology Law Journal
[30] H. Prakken, A.J. Muntjewerff, A. Soeteman, Legal knowledge based systems,JURIX 94, The Relation with Legal Theory
[31] NTT DOCOMO, A Precedent-based Legal Judgement System using Fuzzy Relational Database, Chapter in International Journal of Uncertainty Fuzziness and Knowledge-Based Systems · January 1995
[32] Jayanta Basak, Desmond Lim,"A Feasibility study on automating the automotive insurance claim processing"