Intelligent Intuitionistic Fuzzy with Elephant Swarm Behaviour Based Rule Pruning for Early Detection of Alzheimer in Heterogeneous Multidomain Datasets

Dhanusha C, A.V. Senthil Kumar

Abstract: In this Digital age, a rapid advancement in rise of both communication and information technologies provide many services by incorporating intelligent system of automated health assessment of resident welfare. This is achieved by tracking elderly persons activities using smart home technologies and with this activity-based learning, it helps to discover individuals suffering from early stage of Alzheimer can be predicted without distributing their living style. The main purpose of this paper is to use two different domains of datasets for predicting the alzheimer's in elderly person during its initial stage. Thus, this work uses ubiquitous computing technologies like smart home dataset which collects the daily activities of individuals and as the clinical dataset for prediction of alzheimer's. The objective of this proposed work is to handle the hesitancy of uncertainty by introducing intelligent intuitionistic fuzzy classifier, which inhibits irrelevant rule generation by acquiring the knowledge of elephant swarm behavior (IIF-ESB). Using elephant swarm search behavior, the rules generated by intuitionistic fuzzy are finetuned to ovoid overfitting problem and thus it eliminates the irrelevant rules. The selected potential rules highly influence the accuracy rate of the prediction model in presence of uncertainty. Performance result of the proposed model (IIF-ESB) proved that with the ability to handle the impreciseness in prediction of alzheimer's, the usage of degree of hesitancy and intelligent of elephant swarm searching behaviour increases the accurate prediction rate and decrease the misclassification rate considerably while compared with existing prediction models.

Keywords: Alzheimer, hesitancy, uncertainty, smart home, intuitionistic fuzzy, elephant swarm behaviour

I. INTRODUCTION

In this modern world increasing life expectancy and ageing of population leads to important issues to healthcare systems, due to the shortage of medical staff for patient home care services and increasing cases of people affected by age-related neurodegenerative diseases, such as dementias [1]. One such disorder which is clinically known as Alzheimer is the most common kind of dementia, it happens when the function of brain is no longer works properly.

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In India, around 4 million people are assessed to be suffering from alzheimer and other types of dementia, after china an US which is the sixth leading cause of death, India is in third highest caseload in the world. The India's dementia and alzheimer problem is predict to reach almost 7.5 million during 2030 [2].Alzheimer starts with the symptoms of loss in memory, behaviour and thinking power. In its early stage, dementia signs may be nominal, but as the disease roots more impairment to the brain, the condition of the victim will be worsened. As the nature of alzheimer is progressive it starts from mild memory loss to ability to carry on a conversation and respond of an individual with their environment will be loosen by the individuals. Depending on the individuals the rate of progresses in such disease typically vary but overall, individuals with alzheimer live around 8 years after the symptom for alzheimer begin. At present, there no is proper treatment to stop the progress of Alzheimer's, but there is an option to undergo medications to treat dementia indications. In recent three decades, research on dementia has offered a deep understanding of how the brain gets affected due to alzheimer's. Research on progress to determine the treatments which can effectively cure or prevent alzheimer and of improve the condition of brain.

Alzheimer disease establishes symptoms in multiple areas or domains, like physiology, psychology, cognition and behavior [3]. Based on medical examination on brain imaging and report test produced by psychologists or physicians which is commonly done in later stages, results in deferred diagnosis, but early diagnosis is a main key for effective treatment [4]. Nowadays, smart homes are a developing technological result enabling the monitoring of people's behaviour universally and inconspicuously [5]. Real life data related to action recognition can be collected nonstop throughout the day in an entirely transparent way for the user, which provides a complete view of older adults behaviour change and detection of disorder at the earlier stages in a right time. This smart home-based behavior shifts were plotted to Alzheimer Disease (AD), then the main disadvantage in usual assessment method could be overwhelmed by an early diagnosis of the possible dementia.

The Ultimate goal of this paper is to evaluate the possibility of identifying the psychological, behavioral and cognitive symptoms of alzheimer disease by collecting the smart home behavior data.

Developing Intuitionistic fuzzy Rule classifier-based Alzheimer disease prediction using smart home-based activity recognition.

II. RELATED WORK

In recent years, for monitoring day to day activities of elderly persons using smart home for various medical examination and investigation is greatly attracted by the researchers in the field of clinical data analysis. The information collected from smart home sensors are mostly related to clinical measure such as mobility, sequence of activities, sleep pattern and gait with self-report data, which avoids the need for individual care about the elderly persons. Some of the existing research work relevant to automated smart home based clinical observation using machine learning and mining approaches is discussed in this section

Paavilainen et al. [6] developed a system of monitoring the older adult's circadian rhythm of activities using wrist care system. They performed the comparison in rhythms activity of elderly adults with the collected clinical observation and reported their health status. Another work by this author [7] reported that the relationship among variation in sleeping pattern of demented and non-demented persons over a specific period of time by collecting information using the sensor devices and clinical health assessment. Robben et al. [8] in their work investigated about various high-level features in lieu of location and changeover patterns of an individual's mobility behaviour in indoors with the valuation of motor and process skills.

Suzuki and Murase [9] developed a mini-mental state examination, by observing the indoor and outing behaviour activities, they compared variation in activities and used that information for clinical assessment of their mental health. Rafulla et al [10] in their investigated actual advantages of using smart home analysis by monitoring the daily activities at home and forecasting clinical valuation scores of the residents. To achieve this aim, they developed a clinical assessment using activity behavior method to design a smart home residents' daily behavior and predict the scores based on clinical assessment. This model uses statistical features that explains the characteristics of daily activities of residents using machine learning approaches which predict the assessment score. They evaluated the performance of smart home data gathered from 18 smart homes over two years using classification method.

Zhu et al [11] int their work developed an anomaly detection using wearable sensors to offer an intellectual living atmosphere for elderly peoples. Based on their time, location, activity type, activity transition and duration the anomalies are recognized. For anomaly detection they used maximum likelihood semi supervised learning model with Laplace smoothing. Lotfi et al [12] examined in their work about elderly peoples living independently in real home atmosphere, who were diagnosed with dementia. In this work the authors applied echo state neural network to forecast the sensor activity to alert the caregiver for any anomalous behavior that can be suspected in future. Jakkula and Cook [13] developed an anomalous behavior detection model using smart home data. They used support vector machine to improve the prediction process,

Novak et al[14] designed an artificial anomalous behavior-based activity detection by developing a self-organizing map based classifier. They used changes in daily activities of elderly persons to discover dementia at earlier stages. AneAlberdi et al [15] in their work developed a regression model to predict the symptoms of alzheimer's, whose dataset is collected from activity aware smart home sensor devices. The used Smote Boost and wRACOG algorithm to overcome the imbalance along with feature selection their work mainly contributes to detect early change detection using this technology.Sivaranjani& Senthil [25]developed a health monitoring networks using secure energy aware scheme which work very effectively. Rathi&Senthil[26] introduced an Euler movement firefly algorithm and fuzzy kernel vector machine classifier for keystroke authentication .Illango&Senthil [27] Non Linear Differential Optimization for Quality Aware Resource Efficient Routing in Mobile Ad Hoc Networks.

III. PROBLEM DEFINITION

Due to improved facilities both in living style and advances in medical field, there is a gradual increase of elderly population. But providing caregiver for huge ratio of population is highly impossible because of lack in number of medical staffs or patient home care services, to overcome this difficulty, researchers start focusing on elderly living and well-being toward medical analysis and supporting them for their independent living environment with proper monitoring without disturbing their daily activities. As the advancement in information and embedded technologies using smart home-based elderly people's activity monitoring receives greater response to lead their living atmosphere independently. Still the existing approaches suffers from issues while handling activity based daily living using smart home sensor data and they are as follows:

- ✓ While using Activity based daily living, assessing those datasets collected from sensor dataset are vagueness in nature
- ✓ Smart home-based prediction alone is not the process for predicting the dementia in elderly persons, the clinical assessment must also be used to determine the early signs of alzheimer
- ✓ Existing models are not focusing on uncertainty handling when the daily activities of the victim suffer from multiple signs of cognitive impairments
- ✓ Most of the clustering process involved in prediction of vague datasets often eliminates the border lying instances and the indeterminate instances which are considered as outliers, but those instances may often provide interesting information which influence the performance of prediction process
- ✓ There is so proof on developing a heterogenous multi-domain based alzheimer disease detection

The ultimate goal of this proposed work is to handle the problem of uncertainty when the daily activities of the elderly patients falls under multiple cognitive impairments, indeterminacy in handling continuous values of daily activities, impreciseness in clustering the instances by introducing degree of hesitancy. This paper devised an intuitionistic fuzzy inference model to perform heterogenous multi-domain environment-based Alzheimer Disease Prediction in their earlier stages.

IV. PROPOSED METHODOLOGY: INTELLIGENT INTUITIONISTIC FUZZY WITH ELEPHANT BEHAVIOUR BASED RULE PRUNING FOR EARLY DETECTION OF ALZHEIMER IN HETEROGENEOUS MULTIDOMAIN DATASETS

In this proposed work two different datasets are considered for early detection of Alzheimer among elderly persons. One of the datasets is collected from Centre of Advanced System in Adaptive Systems (CASAS) which comprised of Activities of Daily living (ADL) of elderly persons with the aid of smart home testbeds. Another dataset is gathered from Open Access Series of Imaging Studies (OASIS) repository which is related to MRI data to discover victims with dementia ranging from mild to moderate. Once the dataset is collected, the value of attributes in the datasets are normalized to became them range between 0 and 1. The min-max approach is applied for normalization and it is formulated as follows

$$Norm(x) = (x-min)/(max-min) \qquad (1)$$

Where, x is the value to be normalized and min is the minimum value in that attribute column and max is the overall maximum value.

The detailed description of each process involved in this proposed methodology is explained in the following sections.

A. Dataset Description

The CASAS dataset is collected by utilizing the middleware technology which records the day to day activities of elderly persons living in smart homes, without distributing their daily routines. This work used a single-resident apartment, each with at least one kitchen, a bedroom, a bathroom and a dining area. These rooms are equipped with light and motion sensors on the ceilings along with door and temperature sensors on doors and cabinets. These sensors continuously and inconspicuously screen the daily activities of the residents. The collected information is stored in the data server. Figure 1,displays a sample layout and sensor location for one of the smart home test beds.
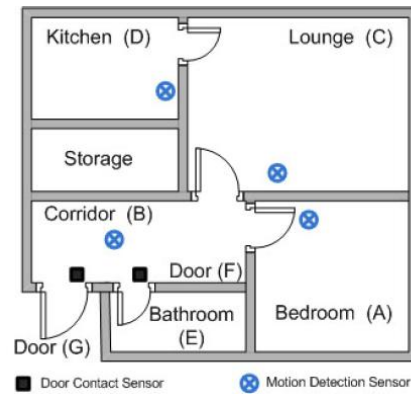

Figure 1 sample smart home layout

OASIS Dataset

OASIS dataset used in this work consist of totally 373 instances with 15 attributes in which 12 attributes along with one class label and remaining two attributes are identifiers comprised in longitudinal dataset [21] as shown in Table 1

Table 1: OASIS Dataset Description

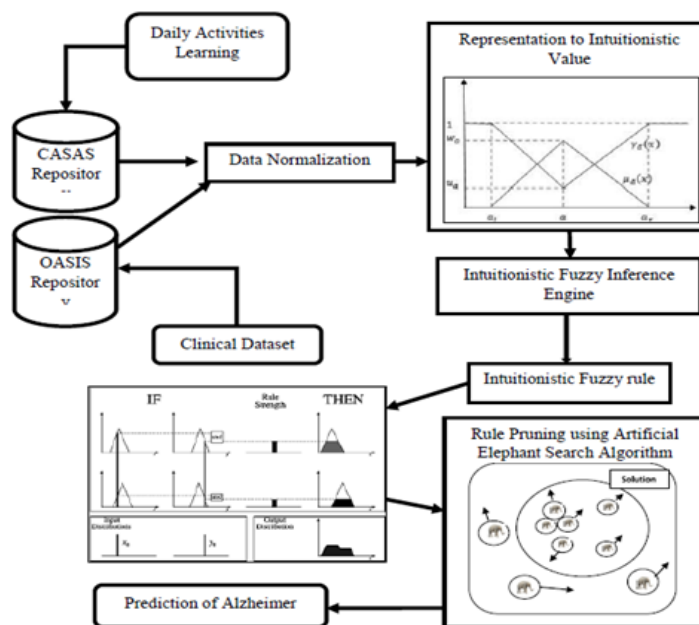|	
1. Patient id	7. Bare Nuclei
2. Clump Thickness	8. Bland Chromatin
3. Uniformity of Cell Size	9. Normal Nucleoli
4. Uniformity of Cell Shape	10. Mitoses
5. Marginal Adhesion	11. Class: (benign, malignant)
6. Single Epithelial Cell Size	

Figure 2 Overall Workflow of Intelligent Intuitionistic fuzzy with elephant behaviour based rule pruning for early detection of Alzheimer in heterogeneous multidomain datasets

As shown in the figure 2, after performing normalization each dataset values are fed as input to the intuitionistic fuzzy inference system and the intuitionistic fuzzy rules are generated with the knowledge inferred from intuitionistic fuzzy inference engine. The resultant rules are optimized by adapting the elephant behaviour based searching, for discovering potential rules involved in prediction of alzheimer in an optimized approach.

B. About Intuitionistic Fuzzy Logic and Classifier

Generally fuzzy theory focuses only on membership element $\mu_A(x)$ and it considers the non-membership element $\nu_A(x)$ value of fuzzy is one minus the membership degree, but it is not true in real time, because there is a possibility of degree of hesitation. So that, the intuitionistic fuzzy sets were developed by [16,17] which includes the degree of hesitancy $\pi_B(x)$, which is defined as

$$W_{IFS} = \{x, \mu(x), \nu(x) | x \in X\} \quad (2)$$

Where both $\mu(x), \nu(x)$ value ranges from 1 to 1 with the condition

$$0 \le \mu(x) + \nu(x) \le 1 \quad (3)$$

If the value of non-membership degree $\nu(x) = 1 - \mu(x)$ then it turns to fuzzy set, but a special case in intuitionistic fuzzy sets announce an added degree to overcome impreciseness in real time dataset of alzheimer prediction, the most exclusive and noteworthy influence which overwhelms the delinquent of lack in knowledge of a specific instance or value which is failed to be focused in fuzzy logic which is known as hesitancy degree $\pi_B(x)$. The inability of fuzzy logic is that, it lacks to overcome the problem of uncertainty in determining alzheimer when there are multiple symptoms of cognitive impairment. An intuitionistic fuzzy set M in X, is inscribed as:

$$\pi_M(x) = 1 - \mu_M(x) - \nu_M(x) ; \quad 0 \le \pi_M(x) \le 1 \quad (4)$$

Due to hesitation degree the value of degree of membership $\mu_z(x)$, and non-membership $\nu_z(x)$ will be less than 1 and while summing them along with hesitation degree $\pi_z(x)$ it will be equal to 1 [18].

This intelligent intuitionistic fuzzy classifier uses three different modules namely intuitionistic fuzzification, intuitionistic fuzzy inference model Intuitionistic fuzzy rule generation.
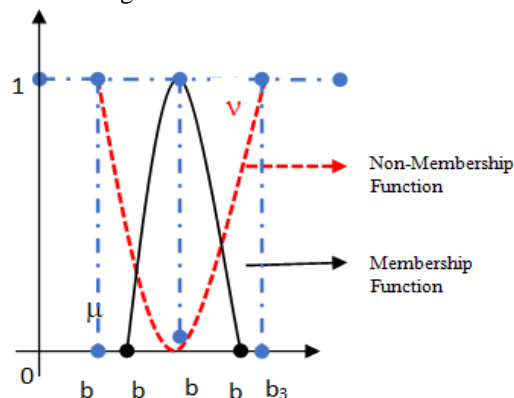
C. Intuitionistic fuzzy representation

The given input value is the dataset of alzheimer disease prediction collected from two different sources so that this research work is used for heterogenous datasets. As the collected dataset are in crisp values before performing intuitionistic inference, the values are converted to intuitionistic domain representation as follows

$$\mu_Z(x) = \begin{cases} \frac{x-b_1}{b_2-b_1}, & b_1 \le x \le b_2) \\ \frac{b_3-x}{b_3-b_2}, & b_2 \le x \le b_3 \\ 0, & otherwise \end{cases} \quad (5)$$

$$\vartheta_Z(x) = \begin{cases} \frac{b_2-x}{b_2-b_1}, & b_1' \le x \le b_2) \\ \frac{x-b_2}{b_3-b_2}, & b_2 \le x \le b_3' \\ 1, & otherwise \end{cases} \quad (6)$$

Where $\mu_Z(x)$ and $\vartheta_Z(x)$ are the membership and non-membership representing the dataset values in intuitionistic domain and it is known as intuitionistic fuzzification as shown in the figure 3.

Figure 3 Triangular Intuitionistic Fuzzy Number Representation

Next, the intuitionistic fuzzy inference model generates the set of if-then rule which is represented as follows

If att_1 is high and att_2 is low and att_3 is low then out is low

Where att_1, att_2 and att_3 are intuitionistic fuzzy input variables, out is a resultant output.

In Intuitionistic fuzzy classifier fuzzy inference system is a main unit having the knowledge of decision making which is its primary task. It generates the decision rule by using IF—Then rules with "AND" or "OR" connectors to provide essential results. The resultant form of Intuitionistic fuzzy inference system is a set of fuzzy rules which converts the crisp input variables into Intuitionistic fuzzy variables.

Next, the intuitionistic fuzzy inference engine underlies the actual intelligence which express the relationship among the input values in the form of if then type intuitionistic fuzzy rules. The rules are comprised of intuitionistic fuzzy logic with its knowledge base and the sample rule are as follows:

IFR1: If SS is high and ASDOT is high and SSDOT is high then diagnosis as normal
IFR2: If SS is high and ASDOT is high and SSDOT is medium then diagnosis as normal
IFR3: If SS is medium and ASDOT is medium and SSDOT is low then diagnosis as Mild Cognitive Impairment
IFR4: If SS is medium and ASDOT is high and SSDOT is high then diagnosis as normal
IFR5: If SS is high and ASDOT is low and SSDOT is low then diagnosis as Alzheimer
IFR6: If SS is low and ASDOT is low and SSDOT is low then diagnosis as Alzheimer
IFR7: If SS is medium and ASDOT is low and SSDOT is low then diagnosis as Alzheimer
IFR8: If SS is medium and ASDOT is medium and SSDOT is medium then diagnosis as other dementia
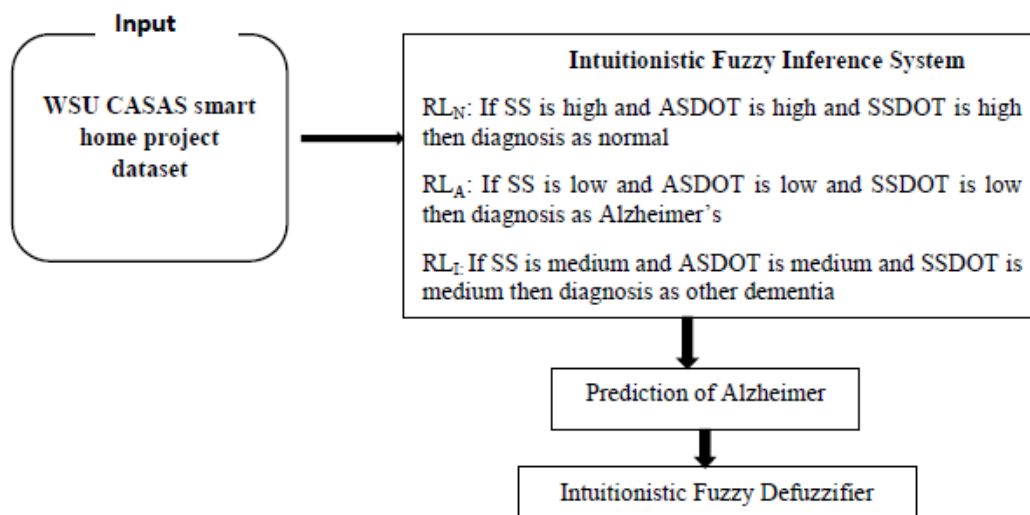IFR9: If SS is low and ASDOT is medium and SSDOT is medium then diagnosis as other dementia

Figure 4 Intuitionistic fuzzy based rule Alzheimer Prediction using Smart home dataset

The intuitionistic fuzzy inference System generates the possible rules, with the knowledge of the expert's rule specification, as the number of inputs grows the generation of the rules will also be increased. All the rules generated by IFS doesn't guarantee to produce correct results, so there is a need to handle such irrelevant rules to maximize the relevancy and minimize the redundancy of rules generated by the standard intuitionistic fuzzy model. Thus, this work introduced an elephant search-based rule pruning models, which helps to select only the potential rules which will greatly influence the prediction of Alzheimer.

D. Optimized Rule Pruning of Intuitionistic fuzzy Rule using Elephant Search Algorithm

One of the general techniques in rule-based classifiers are rule pruning whose task is to reduce the size of the discovered rules by omitting the overfitting data. Such data have a negative effect by misguiding the learning algorithm and generates a very worst classifier performance. During the learning process of a classifier, the algorithm inserts terms to the rule to increase its predictive accuracy by fitting the instances too closely. In this method, the rule will cover the instances which are correctly predicted and those instances are removed from the training set. After that, new instances generate new rule and it leads to perfect classification.

When the rules are produced from noisy instances, they are highly risk, lack of relevancy and expose low predictive accuracy on classifying testing instances. This issue is known as overfitting, which occur when the generate rules tit too well, when they don't have applicability to unseen data, only stick on training instances. Then this will produce negative impact on the classification model. To overcome this problem this research work adapts the behavioral based optimization for rule pruning by using artificial elephant search method for selecting potential rules and eliminating the irrelevant rules which produce negative impact on intuitionistic fuzzy classifier.

E. Elephant swarm intelligence search algorithm

Behaviour of Elephants

Elephant swarm intelligence is a kind of swarm intelligence which is based on water search strategy. Elephants belongs to Elephantidae family, which are the largest terrestrial animals. In nature, elephants live in herds varying from 3 to 35 elephants. Depending on the weather, food, water availability the number of elephants in a herd varies. Living in group plays an important role in finding the resources for living and protecting the herd members. A biggest and oldest male elephant guides a herd, while the female elephant lives only for breeding periodically, the young elephants keep staying in the herd.

Elephants have good memory and exposes advanced intelligence like indication of self-awareness, self-recognition and cognition. They also have advance communication system and sensing strategy by using their sense of smell, vision, hearing, touch and ability to detect vibrations. When they are search of water, they are well equipped to strive for discovering the water resources. They use more than one communication system to search the water resources related to their present conditions. They are very effective for both global and local searching strategy, and they are unselfish and exhibits social behaviour during complex conditions. They communicate and exchange information among the different swarm group for better search solution, which is another important strength of their effectiveness.

There are four idealized rules are used to describe the elephant swarm intelligence for rule pruning they are as follows:

1. Elephants roam around in search of a solution which is termed as elephant swarm, each swarm comprised of number of elephants and all the elephant swarm communication with each other to find the best solution[19, 20]. The head of each swarm is responsible for taking decision about the movement of the group-based on velocity and position.
2. The fitness value and the objective function are directly proportional to the quantity and quality of the rule's strength.

3. They have very sharp memory, hence they can remember the best rules generated by the inference system discovered by its own group known as local best solution so far and the best rules discovered so far by the whole swarm is known as global best solution. Depending on these memories, the elephants swarm can move from one position to another, whereas the velocity and the position are updated during each iteration.

4. A probabilistic constant known as switching probability is used to decide the area for global and local search. The probabilistic decision is taken by the head of the group to shuffle among local search and global search.

For n-dimensional optimization problem the ith elephant group of a swarm position at the t th iteration is represented as

$$Y_{i,n}^t = \{y_{i,1}, y_{i,2}, \dots y_{i,n}\} \quad (7)$$

The velocity is denoted as

$$V_{i,n}^t = \{V_{i,1}, V_{i,2}, \dots V_{i,n}\} \quad (8)$$

i-th group elephant at current iteration, its local best solution is represented as

$$L_{best,n}^t = \{L_{i,1}, L_{i,2}, \dots L_{i,n}\} \quad (9)$$

The global best solution is represented as

$$Gl_{best,n}^t = \{Gl_{i,1}, Gl_{i,2}, \dots Gl_{i,n}\} \quad (10)$$

Initially, the elephant position and velocity are randomly placed in the group of rule space, as the iteration proceeds, it updates the position and velocity according to their rules. The finding activities can happen both at local and global areas. They search for near best instead of far away. To overcome earlier convergence switching probability sp is used among the local and global searches. It chooses global search when a random variable is greater than the probability value, else it performs local search. This random variable overwhelms the earlier convergence to local optima. AS the iteration proceeds the position and velocity values are updated until the certain criteria is met the above-mentioned searching strategy is followed.

The velocity is updated in different ways for global and local search as shown

If rnd> p for global search

$$V_{i,n}^{t+1} = V_{i,n}^t \omega^t + rnd(1,n) \odot (Gl_{best,n}^t - Y_{i,n}^t) \quad (11)$$

If rand ≤ p for local search

$$V_{i,n}^{t+1} = V_{i,n}^t \omega^t + rnd(1,n) \odot (L_{best,n}^t - Y_{i,n}^t) \quad (12)$$

where rnd(1, n) produces a n-dimensional array of random values within [0,1]; $\odot$ signifies element-wise multiplication; ω^t is the inertia weight at present iteration to steadiness between exploration and exploitation. Then, position of an elephant group is modified according to following equation.

$$Y_{i,n}^{t+1} = V_{i,n}^{t+1} + Y_{i,n}^t \quad (13)$$

F. Algorithm for Rule pruning using elephant swarm searching optimization

Begin: Rule pruning Algorithm
Input: Rules generated by Intuitionistic Fuzzy Inference System
Initialize M, n, t_{max}, $X_{,max}$, P and objective function fit-val

For I = 1 to M
Initialize $y_{i,n}$ and $V_{i,n}$

$$L_{i,n} = y_{i,n}$$

End
Estimate fitness value fit-value($y_{i,n}$) for all n elephant group positions
$Gl_{best,n} = min - value(fitness)$
Allot value of ω^t corresponding to the weight update rules as shown in the equation below
For t = 1 to t_{max}
    For i =1 to M
If rnd>p
Perform Global search or update the velocity $V_{i,n}$according to the equation 11
Else
Perform Local search and update the velocity according to the equation 12
End if
Update the position $y_{i,n}$using equation 13
Evaluate fitness value for fit-val($y_{i,n}$)
If fit-val($y_{i,n}$) > fit-val($L_{best,i,n}^t$)

$$L_{best,i,n}^t = y_{i,n}$$

End if
If fit-val($L_{best,i,n}^t$)<fit-val($G_{best,i,n}^t$)

$$G_{best,i,n}^t = L_{best,i,n}^t$$

End if
End for
Y* = $G_{best,i,n}^t$
End for
Return Y* and fit-val($G_{best,i,n}^t$)
End
Output: Pruned Rules of Intuitionistic fuzzy inference system for Alzheimer Prediction

V. RESULTS AND DISCUSSION

The proposed Intelligent Intuitionistic fuzzy with elephant swarm behaviour (IIF-ESB) based rule pruning for early detection of Alzheimer in heterogeneous multidomain dataset is simulated using MATLAB software. This paper uses two different sources of dataset to predict the presence of alzheimer. The CASAS dataset comprised of smart home-based Activity of daily living of elderly patients suspected for cognitive impairments are considered. In Oasis dataset the clinical assessment of elderly persons is considered for alzheimer prediction. The performance of the proposed IIF-ESB is compared with three other classification models such as Radial Basis Function, Multilayer Perceptron, Support Vector Machine and Fuzzy Inference System.

A. Evaluation Metrics

The evaluation metrics used for comparison are precision, f-score and sensitivity and their definition are described as follows:

Precision (prcs)

It is the ratio of total number of instances correctly predicted as alzheimer instances to the total number of instances predicted as alzheimein the alzheimer disease prediction dataset

$$psn = \frac{\text{Tot.No of instances correctly predicited as alzheimer}}{\text{Tot.No of instances predicted as alzheimer}}$$

Sensitivity(sens)

It is the ratio of total number of instances correctly predicted as alzheimer to the total number of instances that are actually alzheime in thealzheimer disease prediction dataset

$$sens= \frac{\text{Tot.no.of instances correctly predicited as alzheimer}}{\text{Tot.No.of instances actuallyalzheimer}}$$

F-**Measure**:

It assiststo measure precision and sensitivity at the same time. It is the weighted average of both the measure precision and sensitivity.

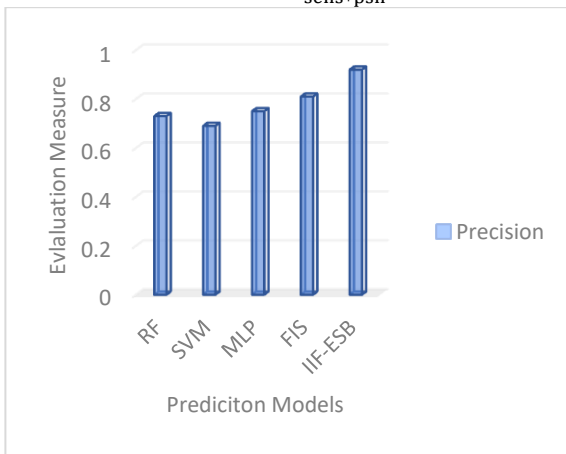$$FMesure=\frac{2*sens*psn}{sens*psn}$$

Figure 5: Performance comparison of five prediction models based on Precision to detect Alzheimer

From the figure 5 it is observed that the performance of the proposed IIF-ESB achieves better precision value while comparing the other three models. The support vector machine produces worst results, where the RF and MLP are placed next it and fuzzy inference system also generates less precision while comparing with proposed model. This is

because the ability of the IIF-ESB in handling impreciseness and intelligence of elephant swarm searching model which prunes the rule greatly influence positive results on alzheimer disease detection compared to the existing models.
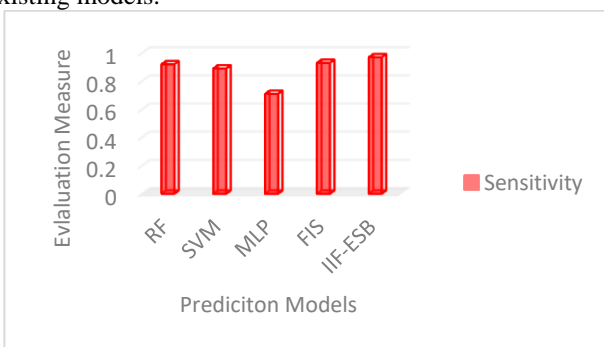

Figure 6: Performance comparison of five prediction models based on Sensitivity to detect Alzheimer

The figure 6 illustrates the performance of the five different prediction models, the output reveals that IIF-ESB based

alzheimer prediction produces better sensitivity while comparing other four models. This is due to the factor that the proposed IIF-ESB includes the information of the vague instances by using the hesitancy degree, where the standard models fail to focus on such imprecise instances with multiple sign of cognitive impairments. When the volume of rule generated by a classifier is high then the problem of overfitting is arise and to overcome this issue this research work used the swarm intelligence of elephants searching strategy to discover more prominent rules and eliminating the irrelevant rules.
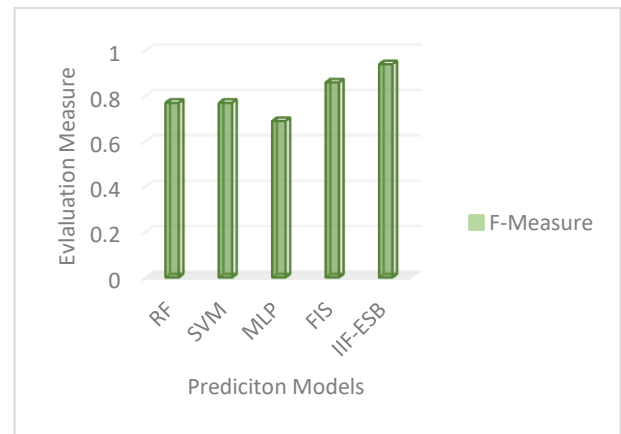

Figure 7: Performance comparison of five prediction models based on F-measure to detect Alzheimer

F-measure is the weighted average of both precision and sensitivity (recall), the figure 7 reveals that the performance of the proposed IIF-ESB based alzheimer prediction yields higher detection rate. The other models RF, MLP, SVM and FIS only concentrates on the instances with precise knowledge when they are considered for vague instances, the fuzzy inference system deals them with degree of membership and other models based on the distribution of the instances they produce result. But the proposed IIF-ESB treats those vague instances as important factors for prediction process and thus it succeeds in treatment of uncertainty.

VI.   CONCLUSION

This paper aims at utilizing both smart home-based data and clinical data for assessing the vulnerability of alzheimer in elderly persons. This work introduced elephant swarm searching behavior to fine tune the rules generated by the intuitionistic fuzzy classifier. The key challenge while performing alzheimer disease prediction, while examining the individuals with possibility of multiple signs of cognitive impairments. Accomplishment and enhancement of the results revealed in this paper is done by collecting more data and by applying optimized bevioural inspiration which produces better results with the ability to handle the imbalanced dataset with early prediction of confirmed cases of transition from healthy state to cognitively impaired elderly adults. In future, different data heuristic methods can be implied with different sources of data.

REFERENCES

1. Ian P. Johnson, Age-related neurodegenerative disease research needs aging models, Front Aging Neuroscience, vol 7, article 168., pp1-2, 2015
2. The Dementia India Report, Prevalence, impact, costs and services for dementia, Alzheimer's and Related Disorders Society of India, 2010 http://ardsi.org/downloads/ExecutiveSummary.pdf
3. Schmitter-Edgecombe M, Parsey C, Lamb R. Development and psychometric properties of the instrumental activities of daily living: compensation scale. Archives of clinical neuropsychology: Journal of the National Academy of Neuropsychologists. Dec; 2014 29(8):776–92.
4. Ouchi Y, Akanuma K, Meguro M, Kasai M, Ishii H, Meguro K. Impaired instrumental activities of daily living affect conversion from mild cognitive impairment to dementia: the Osaki-Tajiri Project. Psychogeriatrics, 12(1):34–42, 2012
5. M. Chan, D. Esteve, C. Escriba, and E. Campo, "A review of smart homes - Present state and future challenges," Computer Methods and Programs in Biomedicine, vol. 91, no. 1, pp. 55–81, 2008
6. Paavilainen P, Korhonen I, Lötjönen J, Cluitmans L, Jylhä M, Särelä A, Partinen M. Circadian activity rhythm in demented and non-demented nursing-home residents measured by telemetric actigraphy. Journal of sleep research. Mar; 2005 14(1):61–68.
7. Paavilainen P, Korhonen I, Partinen M. Telemetric activity monitoring as an indicator of long-term changes in health and well-being of older people. Gerontechnology. 2005; 4(2):77–85.
8. Robben, S.; Pol, M.; Kröse, B. Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing Adjunct Publication – UbiComp '14 Adjunct. New York, New York, USA: ACM Press; Sep. 2014 Longitudinal ambient sensor monitoring for functional health assessments; p. 1209-1216.
9. Suzuki T, Murase S. Influence of outdoor activity and indoor activity on cognition decline: use of an infrared sensor to measure activity. Telemedicine journal and e-health: journal of the American Telemedicine Association. 2010; 16(6):686–690.
10. Prafulla Nath Dawadi, Diane Joyce Cook, Maureen Schmitter-Edgecombe,Automated Clinical Assessment from Smart home-based Behavior Data, IEEE J Biomed Health Inform. 2016 July ; 20(4): 1188–1194
11. Zhu, C.; Sheng, W.; and Liu, M. 2015. Wearable sensor based behavioral anomaly detection in smart assisted living systems. IEEE Transactions on Automation Science and Engineering, 12(4):1225–1234
12. Lotfi, A.; Langensiepen, C.; Mahmoud, S. M.; and Akhlaghinia, M. J. 2012. Smart homes for the elderly dementia sufferers: identification and prediction of abnormal behaviour, Journal of ambient intelligence and humanized computing, 3(3):205–218.
13. Jakkula, V. R., and Cook, D. J. 2011. Detecting anomalous sensor events in smart home data for enhancing the living experience. Artificial intelligence and smarter living 11(201):1.
14. Novak, M.; Binas, M.; and Jakab, F. 2012. Unobtrusive anomaly detection in presence of elderly in a smart-home environment. In ELEKTRO, 2012, 341–344. IEEE
15. AneAlberdi, Alyssa Weakley, Maureen Schmitter-Edgecombe, Diane J. Cook, AsierAztiria, Adrian Basarab, MaitaneBarrenechea, Smart home-based prediction of multi-domainsymptoms related to Alzheimer's Disease, IEEE Journal of Biomedical and Health Informatics PP(99):1-1, 2018
16. Krassimir T. Atanassov, Fuzzy Sets and Systems, North-Holland, Volume 20 (1986), pages 87-96, ISSN 0165-0114
17. Intuitionistic Fuzzy Sets, Krassimir T. Atanassov, Series Studies in Fuzziness and Soft Computing, Volume 35, Springer Physica-Verlag, 1999, ISBN 3-7908-1228-5
18. 25 years intuitionistic fuzzy sets, or: The most significant results and mistakes of mine, KrassimirAtanassov, Int. Workshop on IFS and GN, 17 Oct. 2008
19. Wang, G.G.; Deb, S.; Coelho, L.D.S. Elephant Herding Optimization. In Proceedings of the 3rd InternationalSymposium on Computational and Business Intelligence (ISCBI 2015), Bali, Indonesia, 7–9 December 2015;pp. 1–5.
20. Deb, S. Elephant Search Algorithm for Optimization Problems. In Proceedings of the 10th InternationalConference on Digital Information Management (ICDIM), Jeju, Korea, 21–23 October 2015; pp. 249–255.
21. https://www.oasis-brains.org/
22. Cook, A. Crandall, B. Thomas, and N. Krishnan. CASAS: A smart home in a box, IEEE Computer, 2013.
23. Dawadi, P., Cook, D., Parsey, C., Schmitter-Edgecombe, M., andSchneider, M. An approach to cognitive assessment in smart homes, KDD workshop on Medicine and Healthcare, 2011.
24. Seelye, A., Schmitter-Edgecombe, M., Cook, D., and Crandall, A.Naturalistic assessment of everyday activities and smart environmentprompting technologies in mild cognitive impairment subtypes, Journal of the International Neuropsychological Society, 2013.
25. R. Sivaranjani and A.V.Senthil Kumar "Efficient Health Monitoring Networks using Secured Energy Aware (SEA) Scheme" International Journal of Innovative Technology and Exploring Engineering, Volume 8, Issue 10, August 2019, pp: 3643- 3649 Scopus Indexed,
26. M. Rathi and A.V.Senthil Kumar "Euler Movement Firefly Algorithm and Fuzzy Kernel Vector Machine Classifier for Keystroke Authentication" International Journal of Innovative Technology and Exploring Engineering, Volume 8, Issue 11, September 2019, pp: 2267- 2274 Scopus Indexed,
27. M.Ilango and A.V.Senthil Kumar "Non Linear Differential Optimization for Quality Aware Resource Efficient Routing in Mobile Ad Hoc Networks" International Journal of Engineering and Advanced Technology, Volume 9, Issue 1, October 2019, pp: 1661-1668.

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