Emotional Advisor to help Children with Autism in Social Communication

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***Abstract*- The deficit or impairment in the ability to rationalize emotional states is known as mind-blindness. This condition is seen to be the key inhibitor of social and emotional intelligence for autistic people. Autism is a spectrum of neuro-developmental conditions which affects one's social functioning, communication and is often accompanied with repetitive behaviours and obsessive interests. Inabilities resulting from mind-blindness include gauging the interest of other parties during conversations, withdrawal from social contact, oblivion to social cues, in difference to people's opinions and incomprehensible non-verbal communication. The existing assistive devices and tools mostly serve as remedial tools that provide a learning environment for autistic children to learn about the norms of social behaviour. However, these tools lack the capability to operate in conjunction with real-world situations. An idea is proposed that aims to fulfill this need. We propose a portable device which is able to assist autistic people in communication in real-life situations. We believe that this portable device can help to narrow the gap between us and the world of autism through assisted communication. In this paper, we present one part of this device which is called Emotional Advisor to assist autistic children in engaging in meaningful conversations where people are able to ascertain how they are feeling during communication.**

I. Introduction

Autism Spectrum Disorder (ASD) is a complex neuro-developmental disorder that is characterized by impairments in social interaction such as language skills, in particular, social communication. Unlike most of us, autistic people face tremendous difficulties in understanding social cues and conventions; they are unable to properly express non-verbal communication and body language. These inabilities hinder them from understanding verbal and non-verbal communications, as well as reading human facial expressions effectively. They could not identify and understand the emotions that they are currently experiencing. Without this understanding, they will remain oblivious to other people's intentions, emotions and thus affects their decision-making. The lack of such important prior knowledge of the environment, they hardly make an informed decision. The consequence of such poses challenge for autistic people to socialise in the highly-complex social environment.

In recent years, research on emotion recognition has rapidly increased [1-4]. This phenomenon suggests that the ability to identify and determine one's emotions can serve as an empowerment for the field of artificial intelligence and give rise to smarter, more powerful machines that understands the intention of users. An intelligent machine with emotional awareness can achieve the shortcomings of autistic person. With that emotional awareness, the machine is capable of teaching and guiding autistic people on how to respond appropriately when the person that he or she is communicating with is expressing various emotions. Such machine has the potential to bridge the communication chasm between the society and those diagnosed with autism.

The focus of this research is on the development of a real-time emotion reaction advisor for autistic children that acts as an advisor teaching them how they can act accordingly based on how the other party is feeling during verbal communication. The system generates suggestions for the appropriate response base on the emotion of that person as predicted by the system. The proposed system encompasses two important components: an emotion recognition module and an emotional advisor module. The proposed system consists of a pair of glasses with miniature camera connect to a PDA or a mobile PC. The emotion recognition module operating on the portable device recognizes the facial emotion of the other party and pronounces the emotion through an ear-piece to the autistic user. Besides feedback of the emotional state to the user, the emotional advisor module will display an appropriate advice or suggestion on how the user can respond according to the feeling of the other party. In this paper, development of this emotional advisor is mainly presented. The development of the emotion recognition module can be referred to our published papers in details [6, 7]. The emotional advisor module is essentially a fuzzy rule-based system which forms the database of different types of advises, each corresponding to one or a mixture of emotions that can be exhibited by the communicator. The emotional advisor module will determine which advice to output to the autistic user depending on the input captured by the emotional recognition system. The whole recognition and advising process is real-time and the training is interactive, i.e. the knowledge (database) of the system is updated continuously.

The paper is organized as follows: Section II provides an overview of the computational framework for the emotional advisor using fuzzy rules. A preliminary testing is performed that aims to determine the feasibility of implementing fuzzy logic in the emotional advisor. Section III presents the result of this preliminary testing which outlines the benchmarking process and provides an analysis of the test derivation. Section IV wraps up and presents the conclusion of the project and proposes some possible expansions for future researches.

II. COMPUTATIONAL FRAMEWORK

This research is based on a combination of fuzzy logic, learning and pattern recognition together with a neuroscience understanding of cognitive and visual signal interplay in bridging the communication chasm between autistic children and the world. The methodology of fuzzy sets and membership, reaction-to-emotion association by fuzzification and defuzzification and fuzzy IF-THEN rules are discussed. The research is focused on examining the feasibility of applying fuzzy principles into the emotional advisor. Results from the experiments conducted have shown that the emotional advisor, which forms as one of the modules our proposed intelligent emotion system as shown in Fig. 1, has fulfilled the essential criteria of mobile application: speed and efficiency. The fuzzy system is capable of classifying and generalizing with an accuracy that surpasses various popular classifiers like Naïve Bayes.

This unique characteristic of fuzzy logic is essential in tackling real-world scenarios because the world is full of uncertainty. However, controversies still remain among control engineers whose preferences sway towards two-valued logic and statisticians who only accept Bayesian logic. Nevertheless, fuzzy logic has been successfully incorporated in many of the specialized fields today and it has also been a research topic which is extensively studied over the past few decades. Because of its ability to tame uncertainty, fuzzy logic is a logic theory that suits the nature of our project and can be adopted to fashion the framework of our emotional advisor.

A. *Emotional Inputs*

The three inputs derived from the facial expression recognizer, emotional indexer and prediction are fed to the fuzzy emotional advisors and stored in different text files namely output.txt. ei.txt and predict.txt respectively. Four possible outcomes can be reached for each individual file. Table I shows these possible outputs that can be generated from each text files. A total of 64 unique combinations can be formed based on the different outputs.

In this research, the objective is to test the feasibility of implementing fuzzy logic in the emotional advisor. To achieve this, four different values are deployed for each emotional input. It is to simplify and reduce the magnitude of the prototyping process. The testing is executed in real-time using MATLAB programs. The performance of using fuzzy logic in the emotional advisor is compared and benchmarked against other popular classifiers. Detailed analysis of the output results are discussed and summarized in the later section.

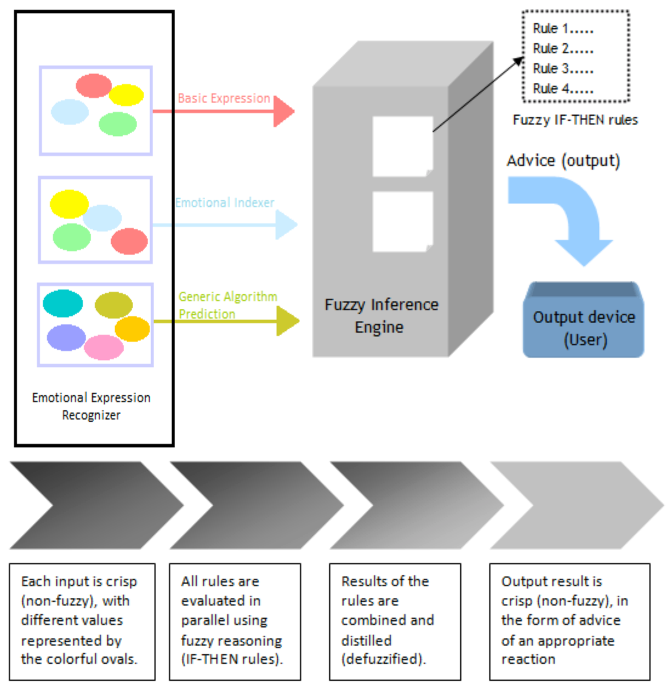

Fig. 1. Block Diagram for Emotion Advisor, which takes facial expression, emotion index and emotion prediction as input and generate advises to user

TABLE I
POSSIBLE OUTPUTS THAT CAN BE GENERATED FROM EACH .TXT FILE

txt.file \ Output Type	Type 1	Type 2	Type 3	Type 4
output.txt	1(neutral)	2(happy)	3(sad)	4(surprise)
ei.txt	NeutralAverage	HappyAverage	SadAverage	SurpriseAverage
predict.txt	1(encouraging)	2(interesting)	3(discouraging)	4(unsure)

B. *Classes and Datasets*

As highlighted earlier, there are 64 unique combinations that can be formed by the 3 different emotional inputs. To determine the number of classes (i.e. the number of possible advices that can be generated) and the number of data combination that the system should deploy, experiments are conducted with different number of classes and data-sets using several classifiers provided by WEKA. From the given results, the number of classes and data-sets to be deployed in the actual test set is determined. This test set will be used for the testing of the fuzzy rules and used for the comparison between all the different classifiers. The results are tabulated and presented in the later section.

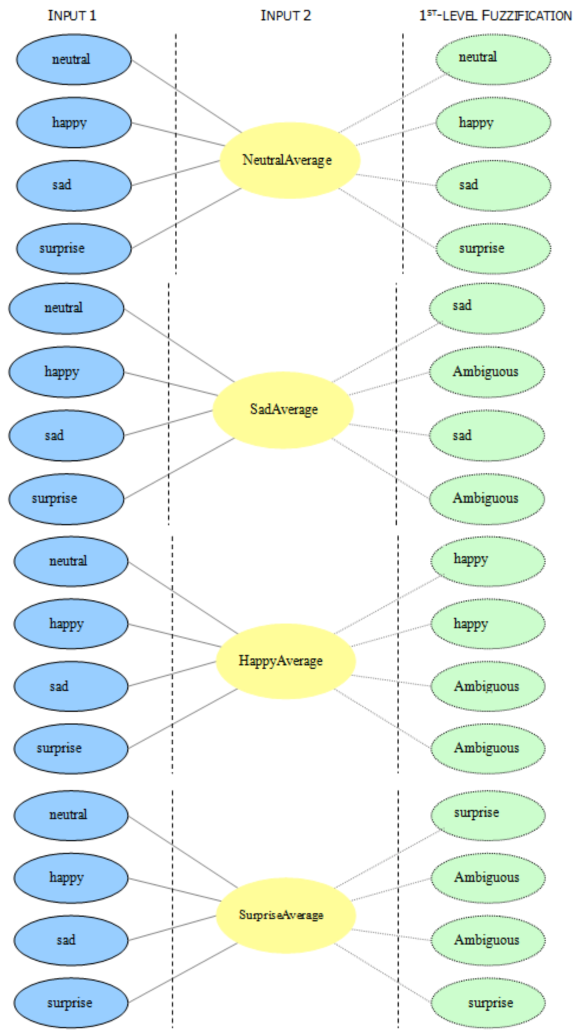

Fig.2. The first-level aggregations of the three emotional inputs, and the resultant truth values of each emotion combination

C. *Fuzzification*

Fuzzification is the process of transforming crisp values into grades of membership for fuzzy sets. The membership function associates a grade to each term defined in the sets. Emotions are complex and vague; hence there is a need to associate each emotional input to a fuzzy set, to accurately pinpoint the overall, dominant emotion that the user is experiencing. Individual may display different reactions towards certain emotions. Therefore, this emotion-to-reaction association is not a one-to-one function. For instance, when one is happy, one may start to sing. Alternatively, others may express happiness by buying an ice-cream for themselves. Both are logical and subjected to the individual's preferences. The following illustrations outline the association between various emotional inputs. Fuzzification is done in two intermediate steps. The output of the first aggregation is fed into the other three inputs, which gives us the final resultant emotional states. Details of the fuzzy reasoning will be elaborated in the later sections. There are two levels of aggregations as shown in Fig. 2 and 3. Fig. 2 shows the first-level aggregations of the three emotional inputs, and the resultant truth values of each combination of emotion. Fig. 3 shows the second-level aggregations of the three emotional inputs, and the resultant truth values for each emotion combination.

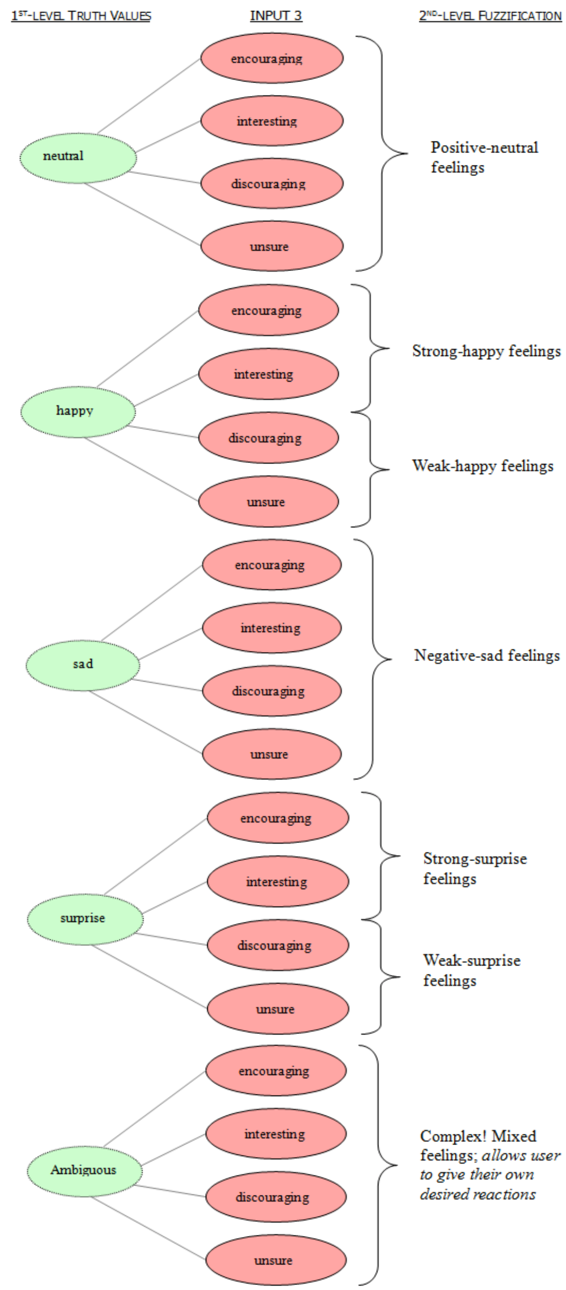

Fig. 3. The second-level aggregations of the three emotional inputs, and the resultant truth values for each emotion combination

D. *Fuzzy IF-THEN rules*

Many practical applications use a relatively restricted yet important part of fuzzy logic which centres on the use of IF-THEN rules. This aspect of fuzzy logic comprises of collection of concepts and methods for handling a diversity of knowledge which can be represented in the form of a set of fuzzy IF-THEN rules whereby the antecedents, consequences, or both, are fuzzy rather than crisp values. The term 'crisp' refers to exactness of an entity. Fuzzy values are defined as fuzzy because they partially belong to one or more sets. A set which consist of fuzzy values is known as fuzzy sets. In essence, the IF-THEN rules convert inputs to outputs, one fuzzy set into another. Fuzzy logic allows the conversion of linguistic control strategy based on expert knowledge, into an automated control strategy. The main beauty is that fuzziness of the antecedents eliminates the need for an exact match with the input, hence giving room for ambiguity which is omnipresent in almost every situation. Given the aggregations, eleven fuzzy rules are designed, capable of predicting the overall emotion state of the user.

Table II shows parts of the fuzzy IF-THEN rules designed for the emotional advisor. These rules are actualized and simulated in the MATLAB program to test the feasibility of real-time generation of reaction-advices. For faster computation, decision-tree structure is administered. By feeding in the sample input data, the experiments show that the program can generate advices smoothly using one-second intervals.

TABLE II
PARTS OF THE FUZZY IF-THEN DESIGNED FOR THE EMOTIONAL ADVISOR (PARTIALLY)

Rule		(Conditions)		Consequences
1	IF	*basic expression* IS a.Strong OR a.Average OR a.Mild	AND	
		emotional advisor is a.Average	OR	
		basic expression IS a.Strong	AND	
		emotional indexer IS NeutralAverage	THEN	generate Very.a advice
2	IF	*basic expression* IS NeutralMild	AND	
		emotional indexer is a.Average	THEN	generate Very.a advice
3	IF	*basic expression* IS NeutralStrong	THEN	generate Neutral advice
4	IF	*basic expression* IS NeutralAverage AND *emotional indexer* is HappyAverage	OR	
		basic expression IS HappyMild OR HappyAverage AND *emotional indexer* IS NeutralAverage	AND	
		prediction IS Encouraging OR Interesting	THEN	generate LittleHappy advice

III. EXPERIMENTAL RESULTS AND DISCUSSION

Because the number of classes used in the testing sets differs, representations of each emotional state are adjusted according to the number of classes that were made available. For each test set, the emotion-to-reaction associations are refined so as the classes made available can adequately differentiate and articulate the resultant emotional state. The resultant emotional state is the truth value obtained by aggregation of the three emotional inputs.

Table III shows the predictive performance using the various combinations of classes and data instances chosen. For instance, Naïve Bayes is shown to have the best results relatively to the other classifiers during the testing of data-set A, with 5 out of 40 corrective classified instances, yield a successful rate of 12.5%. After ascertaining the number of classes and test cases that produces the optimal results, these classes and test cases are assimilated into the fuzzy inference engine and form the actual data-set that investigates the performances of fuzzy logic and other classifiers in their predictive competency. 50 instances were randomly selected and extracted from the entire available combination and formed 8 different sets of data-sets to test the predictive performances of fuzzy rules and other popular classifiers. The results are summarized and shown below.

TABLE III
PREDICTIVE PERFORMANCE WITH VARIOUS COMBINATIONS OF CLASSES AND DATA INSTANCES

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	7, 17.5%	6, 15%	5, 12.5%	6, 15%
Incorrectly Classified Instance	33, 82.5%	34, 85%	35, 87.5%	34, 85%
Root Mean Square Error	0.2996	0.301	0.3179	0.3029
Weighted Avg for TP Rate	0.175	0.15	0.125	0.15
Weighted Avg for FP Rate	0.106	0.121	0.124	0.111

(a) Results for 40 Data, 10 Classes, 3 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	4, 10%	3, 7.5%	2, 5%	5, 12.5%
Incorrectly Classified Instance	36, 90%	37, 92.5%	38, 95%	35, 87.5%
Root Mean Square Error	0.3037	0.3078	0.3141	0.3023
Weighted Avg for TP Rate	0.1	0.075	0.05	0.125
Weighted Avg for FP Rate	0.114	0.127	0.13	0.121

(b) Results for 40 Data, 10 Classes, 7 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	26, 65%	10, 25%	19, 47.5%	10, 25%
Incorrectly Classified Instance	14, 35%	30, 75%	21, 52.5%	30, 75%
Root Mean Square Error	0.3125	0.3841	0.3947	0.3862
Weighted Avg for TP Rate	0.65	0.25	0.475	0.25
Weighted Avg for FP Rate	0.133	0.311	0.187	0.183

(c) Results for 40 Data, 5 Classes, 3 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	31, 77.5%	11, 27.5%	21, 52.5%	16, 40%
Incorrectly Classified Instance	9, 22.5%	29, 72.5%	19. 47.5%	24, 60%
Root Mean Square Error	0.2824	0.3676	0.3612	0.3743
Weighted Avg for TP Rate	0.775	0.275	0.525	0.4
Weighted Avg for FP Rate	0.09	0.224	0.183	0.138

(d) Results for 40 Data, 5 Classes, 7 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	22, 55%	17, 42.5%	17, 42.5%	17, 42.5%
Incorrectly Classified Instance	18, 45%	23, 57.5%	23, 57.5%	23, 57.5%
Root Mean Square Error	0.3811	0.4099	0.4358	0.4161
Weighted Avg for TP Rate	0.55	0.425	0.425	0.425
Weighted Avg for FP Rate	0.293	0.44	0.38	0.396

(e) Results for 40 Data, 4 Classes, 3 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	16, 40%	16, 40%	18, 45%	16, 40%
Incorrectly Classified Instance	24, 60%	24, 60%	22, 55%	24, 60%
Root Mean Square Error	0.3952	0.4138	0.4301	0.4119
Weighted Avg for TP Rate	0.4	0.4	0.45	0.4
Weighted Avg for FP Rate	0.403	0.43	0.347	0.13

(f) Results for 40 Data, 4 Classes, 7 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	33, 66%	19, 38%	23, 46%	27, 54%
Incorrectly Classified Instance	17, 34%	31, 62%	27, 54%	23, 46%
Root Mean Square Error	0.3274	0.3768	0.3804	0.3632
Weighted Avg for TP Rate	0.66	0.38	0.46	0.54
Weighted Avg for FP Rate	0.156	0.395	0.301	0.069

(g) Results for 50 Data, 5 Classes, 3 fold

	Naïve Bayes	AdaBoost	SimpleCart	DecisionTable
Correctly Classified Instance	35, 70%	19, 38%	28, 56%	24, 48%
Incorrectly Classified Instance	15, 30%	31, 62%	22, 44%	26, 52%
Root Mean Square Error	0.311	0.3819	0.3663	0.3699
Weighted Avg for TP Rate	0.7	0.38	0.56	0.48
Weighted Avg for FP Rate	0.148	0.389	0.168	0.12

(h) Results for 50 Data, 5 Classes, 7 fold

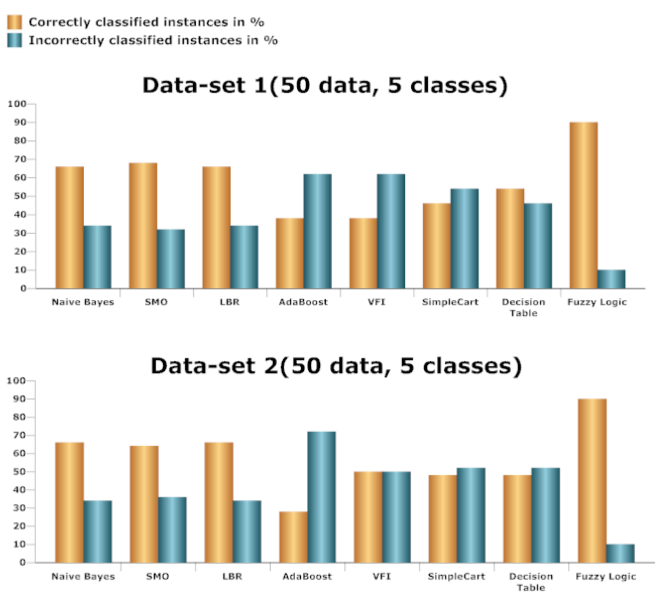

Fig. 4. Results obtained by different classifiers for Dataset 1 & 2

IV. Conclusion

We can conclude that incorporating fuzzy logic in the emotional advisor is a feasible method that can yield a relatively high accuracy in predicting the correct emotional state and generating appropriate advice for the end user. As fuzzy expert systems are modelled empirically, they have the potential to catalyze better performance and are receptive to changes and improvements. The research we present here significantly advances the nascent ability of machines to infer cognitive-affective emotional states in real time from non-verbal expressions of people. By using fuzzy logic in developing a real-time system for the inference of a wide range of emotion states beyond the basic emotions, we have widened the scope of human-computer interaction scenarios in which this technology can be integrated. This is an important step towards building socially and emotionally intelligent machines. In order to implement the emotional advisor in the real-world situation, the standards of the fuzzy rules should be determined by experts in the field of psychology, emotions and autism spectrum disorders to correctly represent and establish the correlation between various emotions, and also to supply suitable reaction-responses which autistic children is able to understand and perform when generated by the emotional advisor.

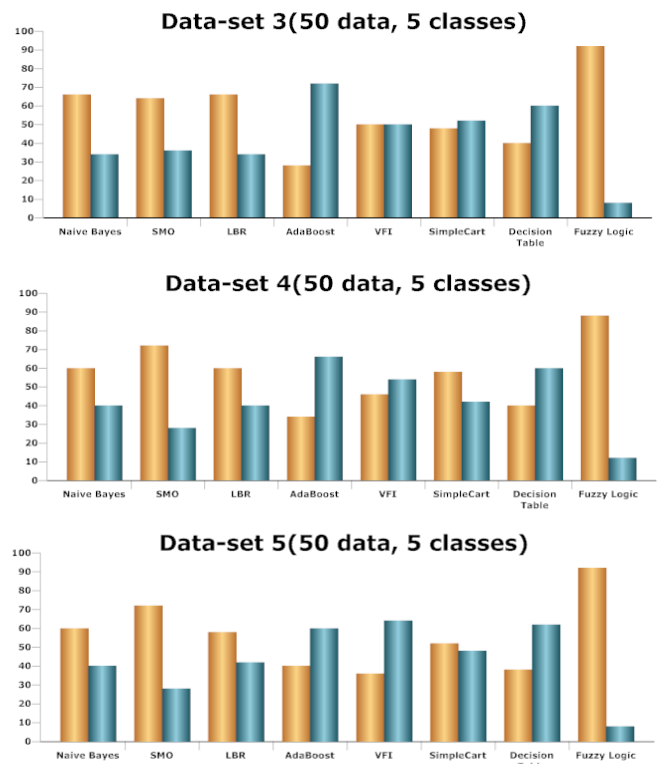

Fig. 5. Results obtained by different classifiers for Dataset 3, 4 & 5

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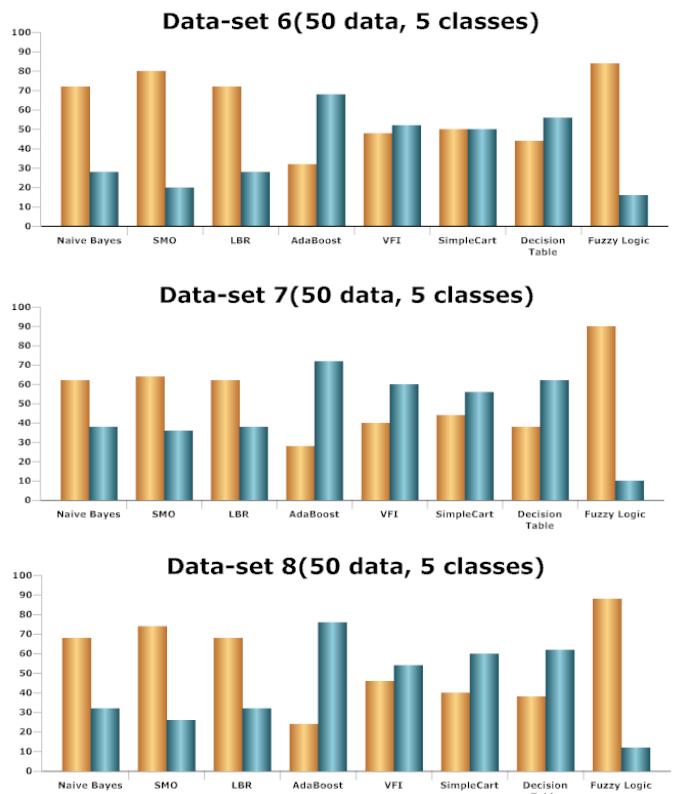

Fig. 6. Results obtained by different classifiers for Dataset 6, 7 & 8