ICORIS2022

The 4th International Conference on Cybernetics and Intelligent System

Kampus Merdeka

UNIVERSITAS POTENSI UTAMA

04th Conference ON ICORIS

INTERNATIONAL CONFERENCE

08-09 OCTOBER 2022

VENUE: HOTEL KHAS PARAPAT, LAKE TOBA
NORTH SUMATERA - INDONESIA

HOST

CO-HOST

SUPPORTED BY

2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031444

2022 Fourth International Conference on Cybernetics and Intelligent Systems (ICORIS)

Medan, Indonesia

(Hybrid Conference)

October 08th-09th, 2022

Part Number: CFP22BWC-ART
ISBN: 978-1-6654-5395-0

2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031589

2022 Fourth International Conference on Cybernetics and Intelligent Systems (ICORIS)

Medan, Indonesia (Virtual)

Phone: +6281263411368

Email: icoris2022@potensi-utama.ac.id

Website: http://icoris.org/

October 08th-09th, 2022

Part Number: CFP22BWC-ART
ISBN: 978-1-6654-5395-0

2022 Fourth International Conference on Cybernetics and Intelligent Systems (ICORIS)

ISBN: 978-1-6654-5395-0

Additional copies of this publication are available from

Curran Associates, Inc.

57 Morehouse Lane

Red Hook, NY 12571 USA

+1 845 758 0400

+1 845 758 2633 (FAX)

PREFACE

Assalaamu ‘alaykum warahmatullahi wabarakaatuh,

After three successful sessions of ICORIS’s conference, we are proud to present the fourth edition of ICORIS. We believe that ICORIS 2022 is an excellent and exceptional opportunity which enables researchers to present and discuss the latest innovations, results and developments in their research topics. This years’ theme is "Build a trusted infrastructure system with blockchain technologies for society 5.0". The conference is expected to strengthen collaboration and provide a forum for academicians, professionals and researchers to discuss and exchange their research results, innovative ideas, and experiences to advance the field of Information Technology, Information Systems and Electronic Engineering in the modern world. The event will incorporate extensive discussions and consist of additional workshops, guest speaker sessions, and scintillating social events that will help our future leaders develop networks and transform their ideas into actions.

The ICORIS 2022 is in the general area of communication and information technology. It provides a forum for presenting and discussing the latest innovations, results, and developments in IT Management & organizations, IT Applications, Cyber & IT Security, and ICT. We present several tracks that are separated into nine thematic areas, each ICORIS 2022 track is a carefully curated selection of sessions and activities focused on an important current or emerging issue. There is 282 papers submission and only 106 papers are accepted to be presented in this Conference. The accepted papers will be presented in one of the regular sessions and will be published in the conference proceedings volume. All accepted papers are submitted to IEEEXplore. IEEE Conference Number: #56380.

On behalf of the ICORIS 2022 committee, we wish to extend our warm welcome and would like to thank all Keynote Speakers, Reviewers, Authors, and Committees, for their effort, guidance, contribution and valuable support.

Wa billahi taufiq wal hidaayah.

Wallahul muwaffiq ila aqwamit-tharieq.

Wasalaamu ‘alaykum warahmatullahi wabarakaatuh.

Husni Teja Sukmana, Ph.D

2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031587

AUTHOR INDEX

2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031402

41	Assed Lussak	145,524,534
42	Astari Retnowardhani	1
43	Asti Herliana	446
44	Atim Djazuli	371
45	Azani Cempaka Sari	77,89,139,194
46	B. Herawan Hayadi	83,248
47	Badrul Munir	189
48	Bagus Made Sabda Nirmala	573
49	Baiq Desy Aniska Prayanti	59,181
50	Bambang Leo Handoko	242,258
51	Baskoro Azis	189
52	Bayu Kanigoro	72
53	Bens Pardamean	19,26,32,37,48
54	Berlilana	376
55	Bhupesh Rawat	213
56	Bob Subhan Riza	286
57	Brandon Nicolas Marlim	238
58	Brian Joe Antoni	184
59	Brilly Andro Makalew	13
60	Bryan Anderson	194
61	Bryan Ghilchrist	342
62	Budi Juarto	202
63	Budi Susilo	512
64	Budi Triandi	335
65	Budi Yulianto	54
66	Burhanuddin Damanik	563
67	Candra Ahmadi	63
68	Carles Juliandy	248
69	Cecilia Valenda	217
70	Charles Bronson Harahap	310
71	Christian Kurniawan	13
72	Cisde Mulyadi	97
73	Cuk Tho	103
74	Daevan Martana	295
75	Dandy Pramana Hostiadi	462,486,491,573
76	Dani Suandi	295
77	Danielson Danielson	194
78	Darmeli Nasution	528
79	David Agustriawan	289,614,621
80	David David	436
81	Davis Inde Satya	230
82	Davy Ronald Hermanus	295
83	Debby Sondakh	625
84	Deby Erina Parung	26

85	Delly Minita Asnathasia	348
86	Dendi Anggriandi	409
87	Dendy Rosman	166,172
88	Denis Eka Cahyani	363,568
89	Denny Alvito Ginting	223
90	Deny Adhar	310
91	Desti Syuhada	63
92	Dewi Khairani	401
93	Dian Amirullah	26
94	Dian Pratama Putra	32,37
95	Dianka Wahyuningtias	172
96	Dickson Ryan Jose	305
97	Didik Dwi Prasetya	568
98	Digdo Sudigyo	37
99	Doni Purnama Alamsyah	330,446
100	Dwi Ramadhona	441
101	Dyah Nur'Ainingsih	584
102	Eben Haezar Ekoputra Soegiarto	625
103	Edgard Jonathan Putra Pranoto	72
104	Edi Syahputra	452
105	Edson Yahuda Putra	275
106	Edy Irwansyah	72,184
107	Edy Victor Haryanto S	436
108	Efa Ayu Nabila	207
109	Egi Rehani Triyulinar	568
110	Eiad Yafi	43
111	Eka Diraksa Putra	172
112	Eka Purnama Harahap	213
113	Eko Setyo Purwanto	77,89,139,194
114	Elena Bianca Jap	77
115	Eli Hendrik Sanjaya	363
116	Elmanani Simamora	452
117	Elsa Aditya	83
118	Erfan Hasmin	282
119	Eri Prasetyo Wibowo	584,591
120	Erna Budhiarti Nababan	405
121	Ernastuti Ernastuti	631
122	Esmi Nur Fitri	599,603
123	Eugene Salim Wijaya	77
124	Evi Dewi Sri Mulyani	500
125	Evi Triandini	395
126	Fadhilah Akhbar	568
127	Fahmi Fahmi	528
128	Fairuz Iqbal Maulana	109,424

129	Faisal Amir Harahap	254
130	Faishal Hilmy Maulida	66
131	Faishal Rayyan	580
132	Farah Levyta	172
133	Farrel Nelson Veriano	295
134	Farrikh Al Zami	599,603
135	Fathi Sei Pahangai Akbar	129
136	Fathur Muhammad Haekal	123
137	Faulinda Ely Nastiti	43
138	Febrianta Surya Nugraha	97
139	Felix Indra Kurniadi	359
140	Felix Pherry	359
141	Felix Ratana	518
142	Firah Putri Pratiwi	500
143	Frans Ikorasaki	254
144	Fransiscus Asisi Agung Dwi Prasetyo Prasetyo	66
145	Freddy Triono	166
146	Fredy Purnomo	238,223
147	Gabriel Flavianus	295
148	Gabriel Janes Posumah	547
149	Gede Angga Pradipta	264,430,462,486,491,573
150	Gerry Giovan	342
151	Giovanna Cheryl Wu	129
152	Green Arther Sandag	625
153	Green Ferry Mandias	275
154	Gregorius Gregorius	359
155	Gregorius Natanael Elwirehardja	19
156	Hana Desy Natalina	166
157	Hardianto	310
158	Helmi Kurniawan	254
159	Henderi Henderi	207
160	Hendra Nusa Putra	286
161	Hendri Julian Pramana	500
162	Heri Gunawan	310
163	Herlina Kikin	512
164	Herlinawati Herlinawati	387
165	Herlino Nanang	401
166	Herman Mawengkang	335,353,528,538
167	Herpri Melinia	414
168	Husni Teja Sukmana	401
169	Hustinawaty Hustinawaty	325
170	I Dewa Ayu Eka Yuliani	512
171	I Gede Surya Rahayuda	554
172	I Gusti Made Karmawan	258

173	I Gusti Ngurah Satria Wijaya	395
174	I Gusti Ngurah Wikranta Arsa	608
175	I Ketut Putu Suniantara	395
176	I Komang Agus Ady Aryanto	264
177	I Made Arya Budhi	608
178	I Made Bhaskara Gautama	608
179	I Made Darma Susila	462
180	I Made Liandana	462
181	I Nyoman Rudy Hendrawan	608
182	Ibnu Darmawan	145,524,534
183	Ida Bagus Ananta Wijaya	424
184	Ida Bagus Ananta Wijaya.	109
185	Ida Bagus Maha Indra Prasada	264
186	IGKG Puritan Wijaya ADH	608
187	Ignatius Ronald	139
188	Ina Sholihah Widiati	161
189	Indrajani Sutedja	123
190	Indriana Indriana	330
191	Irmawan Rahyadi	441
192	I-Shyan Hwang	270
193	Ivan Diryana Sudirman	330
194	Ivan Gananjaya	320
195	Ivana Rosaline Tejakusuma	66
196	Iwan Fitrianto Rahmad	368
197	Jason Sebastian Kusuma	72
198	Jay Idoan Sihotang	480
199	Jefri Zulkarnain	419
200	Jeremy Andrew Jayaseputra	89
201	Jesse Owen Theodore Chandra	320
202	Jesslyn Audrey	320
203	Jimmy Moedjahedy	305
204	Jody Joseph	305
205	Joe Yuan Mambu	480
206	Johann Felix Alexander Christanto	320
207	Joko Pebrianto Trinugroho	48
208	Jonathan Audris Heriyanto	230
209	Jonathan Axel Benaya	217
210	Jonathan Kristanto	359
211	Joshua Oktavianus Tarung Johannis	387
212	Joshua Sun	621
213	Josia Sean Audric Santoso	139
214	Jovianto Godjali	230
215	Juan Constantine	63
216	Julian Alifirman Wardana	202

217	Karli Eka Setiawan	19
218	Kelvin Leonardi Kohsasih	248
219	Kenny Thenjono	518
220	Kevin Halim	72
221	Khawen Flawrenxius	194
222	Khodijah Hulliyah	580
223	Kians Azizatikarna	26
224	Kristianto Wijaya	230
225	Kusrini Kusrini	409,419
226	Langlang Gumilar	363,414,568
227	Lenny Christina Nawangsari	166
228	Lenny Suwondo	424
229	Leonardo Jose Gunawan	238
230	Leonardo Leonardo	202
231	Levana Dhia Prawati	176
232	Lidya Laoh	625
233	Lili Tanti	353
234	Lilik Sugiarto	97
235	Lilis Meliana	258
236	Lilis Yuningsih	486,491
237	Lily Leonita	391
238	Lina Listiani	500
239	Linda Wahyuni	310
240	Louis Ricardo Supit	134
241	Lusiana Efrizoni	286
242	M. Hafidz Ariansyah	599,603
243	M. Wahyu Prasetyo	414
244	Made Liandana	573
245	Mahda Karina	176
246	Maie Istighosah	409
247	Marcello Octavyo Anugrahanto	295
248	Marchel Thimoty Tombeng	270
249	Mardhatillah Shanti	6
250	Mario Donald Bani	289,621
251	Martinus Hanung Setyawan	176
252	Masyhur Dungcik	441
253	Matrissya Hermita	325,591
254	Matthew Austin Naibaho	441
255	Maxrizal Maxrizal	59,181
256	Maya Silvi Lydia	353
257	Michael Siek and Ivana Wijaya	153
258	Moch Firmansyah	289,621
259	Moch. Hari Purwidiantoro	114
260	Mochammad Fahlevi	371,391

261	Mochammad Haldi Widianto	217,320,342,506
262	Moehamad Adi Rochmat	631
263	Moeljadi Moeljadi	371
264	Mohammad Prasanto Bimantio	32
265	Mohammad Rezza Pahlevi	419
266	Muammar Sadrawi	289,621
267	Muchammad Farchan	189
268	Muhamad Yusup	207
269	Muhammad Ikhwanul Atha Labib	387
270	Muhammad Khoirul Wiro	409
271	Muhammad Zarlis	83,368,405,528,538,560
272	Mutiara Sovina	254
273	N. Nelis Febriani Sm	500
274	Nadya Natasya	614
275	Nanda Ihsan Pradana	161
276	Nanda Rizqia Pradana Ratnasari	289
277	Nanda Satya Nugraha	32,37
278	Neil Errando Sutrisno	238
279	Ni Luh Gede Pivin Suwirmayanti	264
280	Ni Putu Linda Santiari	554
281	Niccosan	13
282	Ninda Lutfiani	207
283	Nisya Kintan Qumari	63
284	Normi Sham Awang Abu Bakar	580
285	Nurhasanah Nurhasanah	184
286	Nurhidayanto Nurhidayanto	97
287	Nurul Aini	282
288	Nurul Sukma Lestari	166
289	Octara Pribadi	248
290	Oei Angela Christabel Gunawan	223
291	Oktoverano Hendrik Lengkong	541
292	Oliver Oswin Sumady	184
293	Padma Nyoman Crisnapati	457
294	Patriot Muslim	401
295	Po Abas Sunarya	207
296	Poltak Sihombing	563
297	Prince Siachin Pasombaran	547
298	Purnamawati Purnamawati	301
299	Purnawarman Musa	591
300	Putu Desiana Wulaning Ayu	430,486,491
301	Putu Devi Novayanti	457
302	R. A. Sekar Ciptaning Anindya	584
303	Rachmi Kumala Widyasari	342
304	Rafiqa Dewi	405

305	Rafly Ananda Dwi Septian	213
306	Rahmat Syifana Jaelani	202
307	Rahmi Ramadhani	452
308	Raihan Firas Muzhaffar	591
309	Randy Nasuta	184
310	Rara Sativa	441
311	Ray Tommy	13
312	Regina Carmelita Kristofani	6
313	Restu Adi Wiyono	500
314	Reymon Rotikan	547
315	Reynoldus Andrias Sahulata	305
316	Reza Fauzan	387
317	Rhio Sutoyo	129
318	Rhio Sutoyo.	134
319	Riah Ukur Ginting	563
320	Ribka Xantia Kusuma	348
321	Ricky Aurelius Nurtanto Diaz	264,457
322	Rika Rosnelly	468
323	Rionaldo Alviansa Handoyo	223
324	Risma Yulistiani	223,238
325	Rismayani Rismayani	315,480
326	Rissa Rahmania	230
327	Rita Layona	54
328	Ritu Chauhan	43
329	Riza Wulandari	395
330	Robby Kurniawan Harahap	584
331	Robertus Laipaka	512
332	Robet	248
333	Ronny Ronny	436
334	Roslina Roslina	468
335	Roy Rudolf Huizen	462,486,491
336	Rubianto Rubianto	254,468
337	Ryan Juwanda	77
338	Ryan Matthew	289
339	Ryonaldi Maulana	172
340	Said Achmad	129,134
341	Saifullah Saifullah	387
342	Sal Sabila Wijayanti	409
343	Salsa Nabillah	348
344	Samuel Chandra	223
345	Sandy Kosasi	512
346	Sarifuddin Madenda	631
347	Sarjon Defit	286
348	Satria Perdana Putra Prabowo	161

349	Satrio Arif Budiman	189
350	Sawaluddin Sawaluddin	335
351	Semmy Wellem Taju	275
352	Setiani Putri Hendratno	518
353	Shahrulniza Musa	43
354	Simon	26
355	Sinjiru Setyawan	103
356	Siti Aisjah	371
357	Siti Rihastuti	114
358	Soeheri Soeheri	310
359	Sri Winarno	599,603
360	Stanley Santoso Sandiawan	348
361	Stanley Wisely	217
362	Stenly Ibrahim Adam	541,547
363	Stenly Richard Pungus	541
364	Steven Yanuar Prasetyo Ginting	129
365	Sugiarto	395
366	Suhardi Aras	315
367	Suherman	560
368	Sujono Sujono	59,181
369	Sumarlin Sumarlin	560
370	Sundari Retno Andani	538
371	Sutarman Sutarman	538
372	Suvin Raj Kollabathula	541
373	Syafrizal Chan	166
374	Syafrul Irawadi	181
375	Syaharullah Disa	301
376	Syahazna Balqis Renzaputri	217
377	Syahril Efendi	335,353,560,563
378	Syamsudin Noor	387
379	Tabah Rosyadi	401
380	Taqwa Hariguna	376,381
381	Tavipia Rumambi	325
382	Teddy Suparyanto	32,37
383	Teresa Teresa	109
384	Theodorus Ezra Suherman	506
385	Tinuk Agustin	114
386	Tjeng Wawan Cenggoro	26
387	Tri Handhika	631
388	Tri Widayanti	436
389	Tulus Tulus	405
390	Untung Rahardja	213,512
391	Veronica Livianty	424
392	Vivi Peggy Rantung	480

393	Wahyu sardjono	1
394	Wahyu Waskito Putra	189
395	Wanayumini Wanayumini	83
396	Wayan Cahya Ayu Pratami	395
397	Widi Pangestuti	419
398	Widyastuti Widyastuti	584
399	Willy Lau	139
400	Yohanes Priyo Atmojo	462
401	Yohanes Raynaldi Pereira	348
402	Yovanka Davincy Setiawan	342
403	Yovinne Hendro Cipta	109
404	Yovita Tunardi	54
405	Yudhistya Ayu Kusumawati	6,66
406	Yudi Agusta	474
407	Yuni Yuniar	446
408	Yusfrizal Yusfrizal	254
409	Yustikamasy Astica	419
410	Zakarias Situmorang	83
411	Zefany Athalia	506

TABLE CONTENT

2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031582

Adaptive Neuro-Fuzzy Inference System For Medical Image Classification –A Review

Lilis Yuningsih
Department of Information Technology, Faculty Computer and Informatics
Institut Teknologi dan Bisnis STIKOM Bali
Bali, Indonesia
lilis@stikom-bali.ac.id

Roy Rudolf Huizen
Department of Information Technology, Faculty Computer and Informatics
Institut Teknologi dan Bisnis STIKOM Bali
Bali, Indonesia
roy@stikom-bali.ac.id

Gede Angga Pradipta
Department of Information Technology, Faculty Computer and Informatics
Institut Teknologi dan Bisnis STIKOM Bali
Bali, Indonesia
angga_pradipta@stikom-bali.ac.id

Putu Desiana Wulaning Ayu
Department of Information Technology, Faculty Computer and Informatics
Institut Teknologi dan Bisnis STIKOM Bali
Bali, Indonesia
wulaning_ayu@stikom-bali.ac.id

Dandy Pramana Hostiadi
Department of Information Technology, Faculty Computer and Informatics
Institut Teknologi dan Bisnis STIKOM Bali
Bali, Indonesia
dandy@stikom-bali.ac.id

2022 4th International Conference on Cybernetics and Intelligent System (ICORIS) | 978-1-6654-5395-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICORIS56080.2022.10031548

***Abstract*— Medical image has now been widely used as the object in research particularly in artificial intelligent. Classification automation on medical image can assist to provide information or as the second opinion for the paramedics in doing a medical action and giving a diagnosis for the patients. One of the algorithms as the classifier is the adaptive neuro-fuzzy inference system (ANFIS) method – a hybrid method combining the fuzzy logic and neural network. ANFIS algorithm is the fuzzy inference system (FIS) implemented into the adaptive fuzzy neural network framework. This method combines the explicit knowledge as the representation from FIS and learning ability from the artificial neural network. This paper presents the discussion and the review of the adaptive neuro-fuzzy inference system (ANFIS) algorithm as the classifier in medical image classification. A number of research that have been conducted on the medical image object are evaluated and discussed in terms of their strengths and weaknesses.**

Keywords — ANFIS, Medical Image Classifiaction, Neuro-fuzzy.

I. INTRODUCTION

Disease diagnosis on human in today development has been mostly assisted by means of a system that is able to provide the useful information for the paramedics. The research on the automated diagnosis system have been widely conducted using the medical image data. The medical image can be taken by the paramedics by means of devices such as CT-Scan, USG, or MRI. The main idea or the main purpose of most of the systems proposed is to cope with the human error and more effective diagnosis time and to give information that can help the doctors in taking a medical action. One of the methods used is the adaptive neuro-fuzzy inference system (ANFIS), a set of rules and an inference method combined in a connected structure to later be used to do training and adaptation [1]. Two of models as the adaptive networks that can function as in the fuzzy inference system are ANFIS and Dynamic Evolving Neuro Fuzzy Inference System (DENFIS) [2]. Most of papers on neuro-fuzzy use the backpropagation learning algorithm to generate the fuzzy rules with the function of membership using the Gauss model given separately. This then causes the greater number of parameters to be generated if the number of input variables are added. Mizumoto in research [3] introduced the learning algorithm on neuro-fuzzy without a must to change the form of fuzzy rules. This method is very efficient particularly if used to identify the non-linear functions. ANFIS is an architecture that functionally is similar with the fuzzy rule based on the Sugeno model. The architecture of ANFIS is also similar with the neural network with the radial function with a few of certain limitations. It can be stated that ANFIS is a method in which in doing the rule, the learning algorithm is used to a set of data. In ANFIS, it is also possible to make each rule to be able to adapt. Sulzberger in research [4] developed a method to optimize the fuzzy rules using the artificial neural networks and the development of a new model that enables the translation of the fuzzy rules and function of the membership in the form of network. Osowski [5] developed the neuro-fuzzy through the self-organization learning to the data trained to obtain the optimal number of fuzzy rules and to generate the central of membership function. This paper discusses about a number of researches that used the ANFIS method in classifying the diseases such as cancer [6] [7] [8], tumor [9], diabetes diseases [10], dan optic nerve diseases [11] [12]. In many applications, ANFIS model is used as a classifier in which the input vector of ANFIS model consists of several features extracted from the results of image segmentation. Some discussions about the strengths of ANFIS method and the comparison of the result with other method are presented in this paper.

The rest of this paper is structured as followed. In Section II, we introduce the overview structure and learning algorithm of ANFIS. Section III describes the contibution of ANFIS as a classifier and Section IV describe the conclusion.

II. ANFIS

ANFIS (Adaptive Neruo Fuzzy Inference System) is an architecture that is functionally similar with the fuzzy rule based model of Sugeno. The ANFIS architecture is also similar with the artificial neural network with the radial function with few certain limits. It can be stated that ANFIS is a method in which in doing rule arrangement, it uses the learning algorithm towards

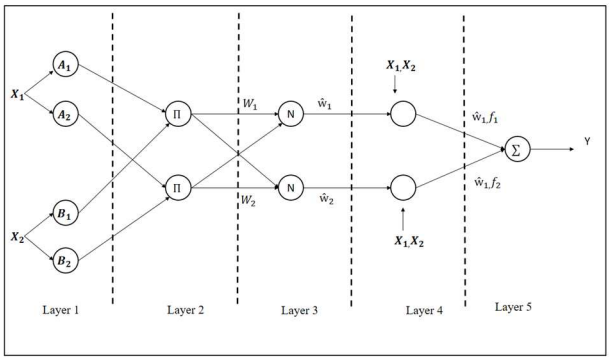

Fig. 1. ANFIS Architecture

a set of data. In ANFIS, it is also possible for the rules to adapt. As stated in book [13] to make the network with the radial base function equivalent with the rule based fuzzy of Sugeno model Order 1, the following limitations are needed:

- The rules must have the similar aggregation method (weighted average or the weighted addition) to produce all outputs.
- The number of activation functions must be equal with the number of fuzzy rules (IF-THEN)
- If there are some inputs in their rule bases, then each activation function must be equal with the membership function of each input.
- The activation function and fuzzy rules must have a similar function for the neurons and the rules existing in the side of its output.

A. Structure of ANFIS

For ease, it is assumed that there were 2 inputs of $x_1 x_2$ and one output y. There are two rules in the basis of Sugeno model [14] :

$if\ x_1$ is A_1 and x_2 is B_1 Then $y_1 = C_{11}X_1 + C_{12}X_2 + C_{10}$
$if\ x_1$ is A_2 and x_2 is B_2 Then $y_2 = C_{21}X_1 + C_{22}X_2 + C_{20}$

If α predicate for the rules to those two rules is w_1 and w_2, then the weighted average can be calculated as follows:

$$y = \frac{w_1 y_1 + w_2 y_2}{w_1 + w_2} = \hat{w}_1 y_1 + \hat{w}_2 y_2 \quad (1)$$

The ANFIS network as shown in Figure 1 consists of the following layers [15] :

1. Each neuron x_i in the first layer is adaptive to the parameter of an activation function. The output of each neuron can be in the form of the membership level given by the membership function of input.
   The output of each neuron is the degree of membership given by the input membership function,

$$\alpha_{A1}(x1), \alpha_{B1}(x2), \alpha_{A2}(x1), atau\ \alpha_{B2}(x2).$$

For example, the membership function is given as:

$$\mu(x) = \frac{1}{1+|\frac{x-c}{a}|^{2b}} \quad (2)$$

Where {a,b,c} refer to the parameters, commonly as b=1. If the values of the parameter changes, then the form of the curve occurred would also change. The parameters in that layer commonly is known as the premise parameters.

2. Each neuron in the second layer is in the form of fixed node whose output is the result of the input. The operator commonly used is AND. Each node represents α predicate from the rulex_i.
3. Each neuron in the third layer is in the form of fixed node as the result of the ratio calculation of the α predicate (w) from the rule i to the number of all α predicates.
4. Each neuron in the fourth layer is the adaptive node towards an output with $\hat{w}_i$ as the normalised firing strength in the third layer and $\{C_{i1}, C_{i2}\ C_{i0}\}$ are the parameters in the neuron. The parameters in the layer is called as the consequent parameters.

$$\hat{w}_i = \frac{W_i}{W_1 + W_2}, \text{ with } i=1,2. \quad (3)$$

5. Each neuron in the fifth layer is the fixed node as the sum of all inputs

$$\hat{w}y_1 = \hat{w}_i(C_{i1}X_1 + C_{i2}X_2 + C_{i0}) \text{ With } i=1,2.. \quad (4)$$

   with $\hat{w}_i$ is a normalised firing strength in third layer and $\{C_{i1}, C_{i2}\ C_{i0}\}$ is parameters in neuron. This parameters in each layer is a consequent parameters.
6. Each neuron in the fifth layer is a fixed node which is the sum of all inputs.

B. Learning Algorithm of ANFIS

In further step, the training of adaptive network was conducted to obtain the values of parameter a and c in equation (2). By taking the value of b=1, then the equation (2) becomes:

$$\mu(x) = \frac{1}{1+|\frac{x-c}{a}|} \quad (5)$$

To improve a and c, error propagation model was used using the concept of gradient descent. For instance, an adaptive network has 5 layers as many as N(L) neuron in the layer L, then the number of error quadrat (SSE) in the layer L data to -P, $1 \leq p \leq N$ is:

$$E_p = \sum_{k=1}^{N(L)} (d_k - X_{L,k})^2 \quad (6)$$

If the form of the adaptive network is as shown in Figure 1, which it only has one neuron in the output layer, then the error propagation to the layer 5 can be formulated into:

$$\varepsilon_{out} = \frac{\partial Ep}{\partial_{x_{out}}} = -2\,(d_{out} - x_{out}) = -2\big(y_p - y_p^*\big) \quad (7)$$

where y_p refers to the target of training data output to -p, and y_p^* refers to the network output to the training data to -p. In the fourth layer, the error propagation has two neurons formulated into as shown as follows in which n5 refers to the neuron in the fifth layer.

$$\varepsilon_n = \left(\frac{\partial Ep}{\partial x_{out}}\right)\left(\frac{\partial f_{13}}{\partial x_{n5}}\right) = \varepsilon_{13}\left(\frac{\partial f_{13}}{\partial x_n 5}\right) = \varepsilon_{out}(1) = \varepsilon_{out} \quad (8)$$

since $f_{out} = \hat{w}_1 f_1 + \hat{w}_2 f_2$, maka $\frac{\partial f_{out}}{\partial(\hat{w}_1 f_1)} = 1$

Furthermore, the error propagation to the 3rd layer has two neurons and it can be formulated as follows in which n3 refers to the neuron that lies in the 3rd layer and n4 is the 3rd and 4th layer.

$$\varepsilon_{n3} = \left(\frac{\partial Ep}{\partial x_{out}}\right)\left(\frac{\partial f_{13}}{\partial x_{n4}}\right)\left(\frac{\partial f_{n4}}{\partial x_{n3}}\right) = \varepsilon_{n4}\left(\frac{\partial f_{n4}}{\partial x_{n3}}\right) = \varepsilon_{n4} f_1 \quad (9)$$

since $f_{n4} = \hat{w}_1 f_1$, maka $\frac{\partial f_{n4}}{\partial(\hat{w}_1)} = f_1$

Furthermore, the error propagation to the 2nd layer has two neurons (i.e. n31 and n32) and it can be formulated as follows:

$$\varepsilon_{n2} = \varepsilon_{n31}\left(\frac{w_2}{(w_1+w_2)^2}\right) + \varepsilon_{n32}\left(\frac{w_2}{(w_1+w_2)^2}\right) \quad (10)$$

if $\varepsilon_{n31} = \frac{w_1}{w_{1+w_2}}$ then $\frac{\partial f_{n31}}{\partial(\hat{w}_1)} = \left(\frac{w_2}{(w_1+w_2)^2}\right)$

and $\varepsilon_{n32} = \frac{w_1}{w_{1+w_2}}$ then $\frac{\partial f_{n32}}{\partial(\hat{w}_1)} = -\left(\frac{w_2}{(w_1+w_2)^2}\right)$

The last one is to the 1st layer in which there are 4 neurons, then the propagation error is presented as follows:

$$\varepsilon_{n11} = \varepsilon_{n21}\left(\frac{\partial f_{n21}}{\partial x_{n11}}\right) = \varepsilon_{n21}\mu_{B1}\,(x_2) \quad (11)$$

$$\varepsilon_{n12} = \varepsilon_{n22}\left(\frac{\partial f_{n22}}{\partial x_{n12}}\right) = \varepsilon_{n21}\mu_{B2}\,(x_2) \quad (12)$$

$$\varepsilon_{n13} = \varepsilon_{n23}\left(\frac{\partial f_{n23}}{\partial x_{n13}}\right) = \varepsilon_{n23}\mu_{A1}\,(x_1) \quad (13)$$

$$\varepsilon_{n14} = \varepsilon_{n24}\left(\frac{\partial f_{n2}}{\partial x_{n1}}\right) = \varepsilon_{n2}\mu_{A2}\,(x_1) \quad (14)$$

Furthermore, the error value can be used to seek the error information towards the parameter a(a_{11} and a_{12} to A_1 and A_2; a_{21} and a_{22} to B_1 and B_2 and c (c_{11} and c_{12} for A_1 and A_2 and c_{21} and c_{22} for B_1 and B_2. From here, the value of the changes in the parameter a_{ij} and c_{ij} (Δa_{ij} and Δc_{ij}) can be determined as follows:

$$\Delta a_{ij} = \eta\varepsilon_{aij}\,x_i \text{ and } \Delta c_{ij} = \eta\varepsilon_{cij}\,x_i \quad (15)$$

where η refers to the learning rate that lies in the interval [0,1]. Thus, the new value of a_{ij} and c_{ij} is a_{ij}= a_{ij} (old) + Δa_{ij} and c_{ij} = c_{ij} (old) + Δc_{ij} (16)

III. ANFIS AS A CLASSIFIER

Neuro-fuzzy systems are the fuzzy systems using the ANNs theory to determine their properties (fuzzy sets and fuzzy rules) by processing the data samples [16]. A specific approach in neuro-fuzzy development is the adaptive neurofuzzy inference system (ANFIS), which has shown some significant results as a classifier in medical image. This section describes the implementation of ANFIS as a classifier in several medical images. However, according to [17] some advantages of ANFIS include

- Refining fuzzy if–then rules to describe the behavior of a complex system
- Not requiring prior human expertise that isoften needed in fuzzy systems, and it may not always be available
- Presenting greater choice of membership function to use
- Bringing very fast convergence time

And according to the [18], ANFIS classifier drawbacks :

- Low accuracy if input vector is large
- Poor classification result if input sample are not enough while there are many nodes in ANFIS.

A. Brain Tumor

A research conducted by [19] proposed a system to detect the brain cancer based upon the shaped-based feature extraction to differentiate the benign and malignant. The input variabel used was the shape distance (SD) and shape similarity measure (SSM) in fuzzy tools and it used the fuzzy rule to evaluate the output. The classifier used was neural network system (NNS), named Levenberg-Marquardt (LM) in which the fed-forward back propagation learning algoritm was used for the pross training of the NN to obtain the status of the brain cancer.

For the classifier, it used neuro-fuzzy tools. The experiment showed a good performance with the feature of SD and SSM obtained from ROI brain tumor lesions. This shape-based feature became a variable input and using the fuzzy rules, this research was able to detect the status of the brain cancer. The method proposed was trained with MR image dataset from 16 cases in which these cases were put into ANN with the structure of 2 input neurons, one hidden layer consisting of 10 neurons, and 2 ouput neurons. From the 16 sample of database, 10 dataset were used as training, 3 dataset were used as the validation and 3 dataset were used as the testing used in the ANN classification. From SSM confusion matrix, it obtained the number of ouput dataset of true positive, false positive dan false negative, namely 6,0, 10 and 0 respectively. Sensitivity, specificity and accuracy of each reached 100%.

Research in [20] provided a proposal to detect the brain tumor using three features: Minimum Gray Level Pixel value occured (MinGL), Maximum Gray level pixel occured (MaxGL) and

TABLE I. COMPARISION RESULT ON [14]

Algorithms	Sensitivity (%)	Specificity (%)	Accuracy (%)
DWT + SOM	95.13	92.02	92.72
DWT + PCA + KNN	96.02	95.03	97.02
Second oreder + ANN	91.42	90.01	92.22
Texture combined + ANN	95.04	96.01	97.22
Texture combined + SVM	97.08	96.06	97.09
FCM	96	93.03	86.06
K-Mean	80	93.12	83.03
Proposed Method (ANFIS)	96.06	95.03	98.67

Mean of Gray level value occured (MeanGL) in the objects of membrane, ventricle, dark abnormality, and light abnormality. Proposed method used three layers of neural network with 500 nodes in the first input layer, 1-50 nodes in the hidden layer, and 1 node in the ouput layer. In the input to the hidden layer, it used the tanh and sigmoid activation function, while in the hidden layer to the output layer it used the log sigmoid function. ANFIS was used as a classifier in which the result showed a better result compared to Fuzzy classifier and BPN as shown in Table 2.

TABLE II. CLASSIFIER COMPARISION BASED ON RESULT [20]

Average Convergence time period (sec)	Average Mean Squared Eror	Average Classification Accuracy %	Classifier
1540	0,1048	93.03	ANFIS
15380	00.25	88.06	Fuzzy
16,245	00.37	85.65	BPN

The combination of neural network and fuzzy logic was also proposed in the research [21]. The object used was the MRI image of Brain tumor using the feature texture adapted using the GLCM method. The classifier used was ANFIS with 2 membership functions and 64 rules frame. The structure of ANFIS used consisted of 6 inputs and a single output. The 6 inputs represented each difference in the feature texture obtained from each image. Each input was given two generalized beell curve membership function and the output was represented with two linear membership functions.

The total 161 nodes were used in this architecture. The result of the proposed method was then compared to other two classifiers: BPN and fuzzy classifier. With the result showing that ANFIS was able to obtain the accuracy of 93.3%, then, this value was higher than that of BPN and fuzzy classifier. Research [22] used the ANFIS model as a classifier to detect the brain tumor. The feature of Gray Level Co-occurance Matrix (GLCM) was used to differentiate the abnormal and normal brain tumor. The result of the proposed method was then compared to the result of Fuzzy C Means (FCM) and K Nearest Neighbors (KNN) method. The result showed that the performance of ANFIS as the classifier was better by achieving the values of accuracy of 98.67%, sensitivity of 96,6%, and specificity of 95,3%. These results were higher than that of the methods of FCM and KNN as shown in Table 2.

A research [23] used the feature of GLCM and dual tree complex wavelet transform multi-scale decomposition differentiating the stages from the brain tumor into benign, malignant, and normal. ANFIS was used as a classifier. Different from the research in [24] using the Principal Component Analysis (PCA) method to extract the feature in differentiating the MR image in the normal and abnormal brain. The classifier used ANFIS with seven neurons connected to seven features. The output layer consisted of one neuron differentiating whether it was included as normal and abnormal. A research [25] used ANFIS as a classifier to detect the existence of tumor of Glioblastoma Multiforme (GBM). The architecture used in the research can be seen in Figure 2 as follows.

Furthermore, research in [26] used the neural network, fuzzy cluster method to identify the abnormal brain tumor region on the MRI image. The spatial fuzzy clustering method was applied to detect the brain tumor part in the MRI scanning images. In the classification stage, BPFNN has been implemented to find the brain tumors in images. This proposed Back Propagation Fuzzy Neural Network classifier technique has been used to classify the benign and malignant brain tumor images. The result showed that BPFNN classifier could provide a fast and accurate classification compared to other neural network methods and it could be effectively used for classifying the brain tumor with the high level of accuracy. A research in [27] used the Non-Sub Sampled Countourlet Transform (NSCT) to enhance the brain image and it used the texture feature later to be trained using the ANFIS classifier. The object used was the brain image that identified the disease of Glioma brain MRI image. Table 3 shows the summary of the results and some parameters used in the research using ANFIS as the classifier to detect and classify the disease in the brain.

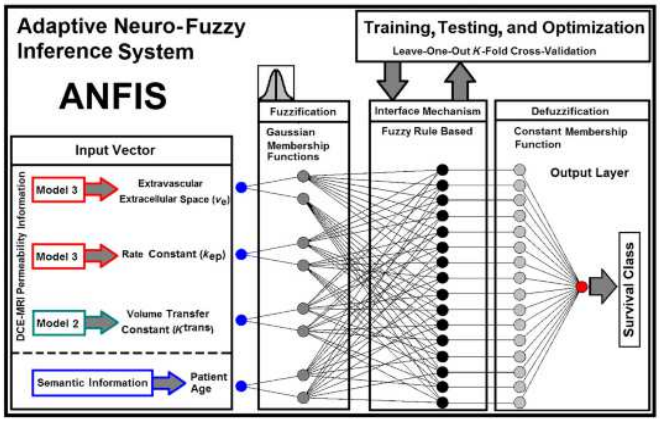

Fig. 2. Adaptive Neuro-fuzzy Inference System (ANFIS) structure and flow information for glioblastoma multiforme (GBM) [25].

B. Breast cancer

A number of artificial intelligent techniques have been applied in radiology to make a prediction and assessment to the biopsy in the breast cancer. Some of techniques that have been developed include the ones using Artificial Neural Network, Convolutional Neural Network, Radial Basis Network, General Regression Neural Network, and Hybrid technique between fuzzy logic and Neural network known as Neuro-Fuzzy [28]
One of the develop of Neuro-Fuzzy concept is known as the Adaptive Neuro-Fuzzy Inference System (ANFIS), where it is able to connect functions existing in a set limited to any levels. In journal written by Huang et al. (2010), classification in the dataset of breast cancer taken from the UCI machine Learning Repository Mammographic Mass consisting of BI-RADS assessment, patients age, and BI-RADS attributes with ground truth from 516 benign and 445 malignant mass was conducted [29]. ANFIS was used to build a model of classification prediction between malignant and benign with an architecture consisting of 5 layers in which layer 1 functioned to generate the membership grades for each set of input data vectors, layer 2 implemented the fuzzy AND operator, while layer 3 acted to scale the firing strengths. The output of layer 4 was comprised of a linear combination of the inputs, multiplied by the normalized firing strength w: $Y = w(pX + r)\ y$ where p and r were the adaptable parameters, and layer 5 was a simple summation of the output of layer 4. The training process consisted of two-pass process by using the number of each epoch, output resulted from layer 4 and 5 calculated using the least-square regression method, and the output of the ANFIS was calculated and the errors propagated back through the layers to determine the premise parameter (Layer 1) updates, This research showed the result with the performance of the ROC value of 92.80%, compared to the other classifier methods such as PSO based ANN with only by 91.10%.

ANFIS model with hybrid learning algorithm was also used by Fatima et al. (2012) to classify the breast cancer with the dataset taken from University of California Irvine (UCI) Machine Learning Repository consisting of 699 data with 65.5% classified as benign and 34.5% as malignant. Here, the hybrid learning algorithm was used to identify the existing parameters in ANFIS in which the learning algorithm referred consisted of 2 phases: in the forwarding process to the hybrid learning algorithm, node outputs values going forward until layer 4 and the consequent parameters were identified by the least square method, and when the backward passes, the premise parameters were adjusted using the gradient descent method. The result of the research showed that the hybrid method as the combination of back propagation and least square has given a better result with the accuracy of 98.25% in comparison to the

TABLE III. SUMMARY RESULT ON ANFIS CLASSIFIER ON BRAIN DISEASE

Result	Dataset	Stucture & Parameter	Feature	Algorithm
Sensitivity, specificity and accuracy and accuracy: 100% , TP,FP,TN,FN : 6,0,10,0	MR Image	Three layer NN (one input,one hidden layer,one output) feed forward with 2 input sigmoid hidden neurons and linier output neurons. 10 number of hidden neuron	Shape distance (SM), Shape Similarity measure (SSM)	Levenberg-Marquardt (LM), ANFIS classifier, and ANN Classification
Classification Accuracy:93.3% mean squared error : 0.151	MR Image	tiga layer neural network 500 nodes on first input layer, 1-50 nodes on hidden layer, dan 1 node on output layer. tanh sigmoid activation function and log sigmoid function	MinGL,MaxGL, MeanGL. (membrane,ventricle,dark abnormality,dan light abnormality	ANFIS
Accuracy Classificartion : 93.3% convergence time period : 1549 sec	MR Image	membership function adalah 2 dan menggunakan 64 rules frame Struktur dari ANFIS yang digunakan terdiri dari 6 inputs dan single output and total ndes 161 iteration number 200. Step for parameter adpation 0.01 dan error tolerance 0.001.	Texture Feature (GLCM)	ANFIS
Accuracy Classification : 98.67%	MR Image	7 inputs and single output with 16 fuzzy rules Input with bell curve membership function and output linear membership function	Texture Feature (GLCM)	ANFIS
The CCF :84.8%. High diagonal elements of the confusion matrix (81.8%, 90.1% and 81.8% for Class 1, Class 2 and Class 3, respectively)	DCE-MRI	K-fold cross-validation (K = 33) technique was employed for training, testing and optimization of ANFIS	PK Parameters	ANFIS And Nested Model Selection
Acc : 90%,Sensitivity : 100%,Specificity : 75%	MRI Images	nodes in the input layer is 9 representing features extracted from the ROI. The number of nodes in the hidden layer is 5 was decided experimentally, The network is trained using log-sigmoid activation function with a learning rate of 0.1	Texture Feature (GLCM)	Back propagation Fuzzy Neural Network
- Acc : 98.5 %	MRI Images	single input and output layer with five intermediate hidden layers, each hidden layer have 10 neuron	Texture Feature (GLCM), Law's texture	ANFIS

one only using the back propagation that only obtained the accuracy of 64.91%. The further research was conducted by Ashraf et al. (2010) using a proposed approach that is Information Gain ANFIS or known as IGANFIS [30]. The Information Gain aims to select the attributes or features with the highest values in which there were total 9 attributes or features taken from Wisconsin Breast Cancer Diagnosis (WBCD) with 699 record data. The output of information gain was the input feature that would be used in ANFIS as the

training and testing data. The result obtained from the proposed approach showed the accuracy of 98.24%. This research also conducted a comparison of the testing towards a number of methods that is ANFIS proposed by Atashi et al. (2017) [31] with the accuracy of 59.90% and SANFIS with accuracy of 96.07%. The development of the hybrid method in neuro-Fuzzy has always been being conducted. In 2016 Elloumi

et al. conducted an approach named Self-Constructing Neuro Fuzzy (SCNF-PSO) [32]. This algorithm used the self-constructing method to determine the number of rule J and to connect the antecedent and consequence parameter by considering 9 input parameters as the reference in the method proposed. Thus, in SCNF classifier, it could generate the output that can do the classification of benign (with the value 0) or tumor (with the value of 1), and PSO algorithm implemented to seek the most optimal value from the antecedent and consequence parameter Maximizing the object of the function. PSO algorithm executed to reach the maximum value from the objective function or the maximum number of iterations. This phase obtained the optimal parameter value in SCNF classifier, To obtain the best performance of the classification process, then an objective function for the particle m: $H\ (P^{(m)} = \alpha.ACC + \beta.Se + \gamma.Sp$ was defined in which α,β and γ were represented from the weight of overall accuracy from the classification process (ACC). *Se* refers to sensitivity and *Sp* refers to the specification and $P^{(m)}$ is the particle of position vector by the concatenation of the antecedent and consequence Parameters of all obtained rule. Using the dataset from Wisconsin Breast Cancer Diagnosis (WBCD) through the method approach proposed, it obtained the accuracy level of 99.12%. The method development in diagnosing the breast cancer furthermore was proposed by Liang et al. (2017) using the hybrid method namely Information Gain method and the subtractive clustering adaptive neural fuzzy inference system (IG-SCANFIS) [33]. Information gain method was applied to reduce the dimension of the attribute of feature and to apply the feature attribute previously selected as the input attribute in SCANFIS. In other words, the Information Gain was used as the method in selecting the features to be used as the input. The method and SCANFIS controller used the Sugeno fuzzy rules and the weighted sum method to calculate the total output, and eliminate the need for a large amount of computational work to clarify the conventional fuzzy system center of gravity method. Thus, the data processing was minimized, and according to the neural network Self-learning characteristics, it could improve the performance of fuzzy systems. The accuracy obtained from the proposed method was 99.44%. The summary of the result on ANFIS classifier on Breast disease is presented in Table 4.

TABLE IV. SUMMARY RESULT ON ANFIS CLASSIFIER ON BREAST CANCER

Author	Algorithm	Result	Dataset
		Accuracy	
Fatima et al (2012)	Last square and backpropogation	98.25.00	University of California Irvine (UCI) 699 dataset
Huang et al (2012)	Last-square regresion and backpropoagation	92.08.00	University Erlangen- Nuremberg (961 dataset)
Ashraf et al (2010)	Information Gain ANFIS	98.24%	Wisconsin Breast Cancer Diagnosis (699 dataset)
Elloumi et all (2016)	ANFIS and PSO optimation algorithm (SCNF)	99.12%	Wisconsin Breast Cancer Diagnosis (699 dataset)
Atashi et all (2017)	ANFIS	94.44%	Wisconsin Breast Cancer Diagnosis (699 dataset)
Liang et all (2017)	Information Gain Subtractive ANFIS (IG-SANFIS)	99.44%	Wisconsin Breast Cancer Diagnosis (699 dataset)

C. *Retinal vessel*

As a classification method, ANFIS was also applied on retinal image with one of purposes is to analyze the object on the retinal image to analyze the form of the blood vessel on the retina. The result of the analysis could be used as an initial step to diagnose and detect the Diabetic Retinopathy for the patients of diabetic disease. Several research related to detecting blood vessels in the retina have been conducted using various methods, especially in the classifier method such as Bayesian classifier by approaching the level set to detect the thick vessels in the retinal image where the accuracy obtained by this method reached 95.29% [34], and with SVM classifier achieving the accuracy of 95.1% [35]. Based on the results obtained from the accuracy of the classifier method, Prakash et al, (2017) proposed a model approach with multilayer classifier ANFIS to obtain the better accuracy. The proposed approach model showed 98.45% accuracy based on the public datasets of DRIVE and STAR[36]. The high accuracy achieved in the classification process cannot be apart from how to do the data pre-processing in the data where each pixel in the retina fundus image was expressed with 8D-feature vectors v = {f1, f2, f3, f4, f5, f6, f7, f8. The extracting gray level features included f1, f2, f3, f4 and f5, F6 representing the extracted orientation feature, f7 represented the extract morphological feature, and f8 represented the Gabor feature extract.

This factor is an input in the classifier. Classification process produced 2 classes: vessel pixel or non-vessel pixel. To improve the accuracy of the classifier, the design of ANFIS used multilayer, which consisted of input layers, multiple hidden layers with a single output layer. A multi-scale scale

transformed the images from the retina into a number of features where a number of extracted features was similar with the number of neurons in the input layer.The results of the accuracy was improved using the hidden layers, each of which was built by setting 15 neurons after several iterations. Single neurons at the output layer classified each pixel in the retina image. Borah (2015) utilized ANFIS as a classifier method for retina recognition. The structure of ANFIS used consisted of 5 layers where the first layer performed fuzzification, and the second layer generated the response of the network due to fuzzy inputs. The third layer performed normalization. For the fuzzy responses, adaptive update was done by the fourth layer. The last layer performed the task of summation of all the outputs[37]. The fuzzification on the first layer used Generalized Bell MFs and Gaussian MFs. Gaussian functions are well known in the fields of probability and statistics; they possess some useful properties such as invariance under multiplication and Fourier transform. The bell MF has more parameters compared to the Gaussian MF, so it can approach a non-fuzzy set if b→∞[38]. For the ANFIS training method, it uses Least-square with the back propagation gradient descent with the average of training using 10-200 epoch and total 10 membership functions. The ANFIS model proposed was able to reduce the epoch by 50%, and the training time required was in the range of 1.9- 2.1 for each sample compared to ANN method and the accuracy obtained with ANFIS classifier was 95%, This paper provides a suggestion for further research on how to make an improvement in the architecture of ANFIS to increase the accuracy. The comparison of the accuracy of some methods that have been presented with the subject of retinal blood vessel showed the performance of the ANFIS classifier with the highest accuracy as shown in Table 5.

TABLE V. COMPARASION RESULT IN DIFFRENT CLASSIFIER FOR RETINAL VESSEL

Author	Algorithm	Result	Dataset
		Accuracy	
Xiao, 2013	Bayesian classifier	95.29%	DRIVE and STAR
Siva, 2014	SVM classifier	95.10%	DRIVE and STAR
Borah, 2015	ANFIS classifier	95%	DRIVE and STAR
Prakash, 2017	ANFIS with multiple layer	98.54%	DRIVE and STAR

D. Servic cancer

The paper written by Al-batah (2014) related to the cervical cancer into 3 classes: normal, low-grade squamous intraepithelial lesion (LSIL) and high-grade squamous intraepithelial lesion (HSIL) based on the recognition using Multiple Adaptive Neuro-Fuzzy (MANFIS) [39] in which the architecture of MANFIS had 6 input of *X1,X2,X3,X4,X5,and X6,* and 3 output of *f1, f2 and f3*, as shown in Figure 3. A hybrid learning algorithm which combines least squares estimation and back propagation is used for membership function parameter estimation. The advantage of hybrid method is that it uses back propagation for parameter associated with input membership function and least square estimation for parameters associated with output membership. Total 500 single cell images were used in the classification process (376 normal, 79 LSIL and 45 HSIL) in which 80% of total images (400 images) were used for the data training and 20% (100 image cells) were used as the data testing.

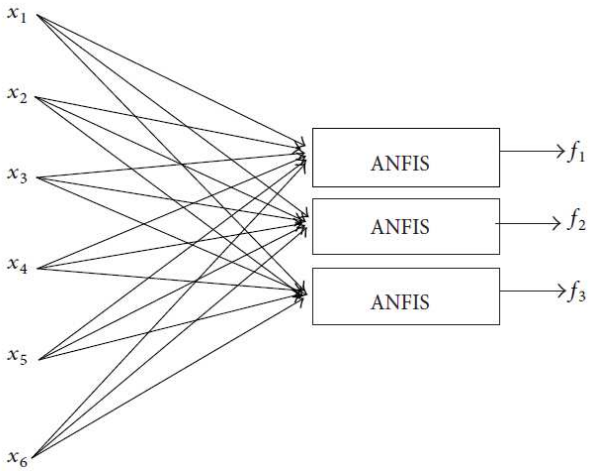

Fig. 3. The architecture of the MANFIS

The accuracy percentage of each class was calculated by dividing the summation of the predicted number of cells over the summation of the original number of samples in each of all folds (k-fold = 5) and produced the results for overall classification process of 96.3% and 94.2% for training and testing phases.

E. Thyroid

Thyroid is an important gland located in the lower neck producing hormones and affects every cell in tissue, and regulates the metabolism in the body. The excessive hormone production can result in some disorders in body such as nervousness, muscle weakness, unexplained weight loss, sleep disturbances and vision problems. Based on the surveys, 20 billion people suffer from thyroid swelling or thyroid cancer. To earlier prevent and find out the condition of this thyroid gland, a diagnosis is needed regarding this disease. Useful knowledge can be extracted from the database where a significant amount of relevant data is stored. Some studies related to how to diagnose thyroid conditions can be done by studying the image from the thyroid data itself. Some that can be done are image processing and classification. One of the studies that have been done is Waheed (2017) with a new decision-based hybrid system, the proposed system consisting of three stages.

In the first stage, 25 features of the dataset (retrieved from the University of California Irvin machine learning repository) were reduced using Information Gain method to avoid data redundancy and reduce computation time. In the second stage, the missing values in the dataset are dealt with k-Nearest Neighbor (k-NN) weighting pre-processing scheme. Finally, the resultant data was provided as input to Adaptive Neuro-Fuzzy Inference System for the purpose of input output mapping in the last stage for system [40], the classification accuracy for the Information Gain Adaptive Neuro Fuzzy Inference System (IG-kNN-ANFIS) to diagnose thyroid disease was calculated as 99.1%, as the highest accuracy ever recorded compared to Hui-Ling et al. (2012) using FS-PSO-SVM reaching only the

accuracy of 98.59.

Research conducted by Soumya et al. (2015) [41] proposed an automatic classification for kidney diseases in ultrasound image. The classification was divided into four types: Normal, Cyst, Renal Failure and Angiomiolipoma. The features used were the statistical features and set of multi-scale wavelet-based features taken from the ROI of the test image. The PCA was then used to reduce the number of features. ANFIS was used as a classifier with two hidden layers, each of which contained 10 neurons and five output nodes. A Sanger's rule and sigmoid activation function were used in the ANFIS learning process. The tolerance limit for errors used (a mean square error) was 0.05 for the end of learning limit. The results showed the correct classification rate reaching 92% using multi-scale wavelet-based features

IV. Conclusion

In this work, we present a review about the hybrid method called as ANFIS in the medical image area. In this review, ANFIS was used as a classifier in the model proposed in the reference of this research. Overall, ANFIS was able to give a satisfying result in comparison to other methods in the test. The learning ability owned by neural network, the existence of a set of rules and an inference method combined in a connected structure could make this method able to adapt in a set of dataset given. However, the research results that have been reviewed from a number of reference sources showed some drawbacks in this method. The more number of data inputs could reduce the accuracy of the performance of this method. Conversely, the ANFIS performance would be improved with the sufficient number of input samples and the addition of the nodes in the hidden layer of ANFIS. However, it certainly takes more time for computation. In general, the performance of classifier would be dependent upon several factors such as size and quality of training set, the imported training rigor and parameters chosen to feed to ANFIS as the inputs can affect the classifier performance.

References

[1] Kasabov, "Evolving Neuro-fuzzy Inference System." 2002.

[2] N. K. Kasabov and Qun Song, "DENFIS: dynamic evolving neural-fuzzy inference system and its application for time-series prediction," *IEEE Transactions on Fuzzy Systems*, vol. 10, no. 2, pp. 144–154, Apr. 2002.

[3] Y. Shi and M. Mizumoto, "A new approach of neuro-fuzzy learning algorithm for tuning fuzzy rules," *Fuzzy Sets and Systems*, vol. 112, no. 1, pp. 99–116, May 2000.

[4] S. M. Sulzberger, N. Tschichold-Gurman, and S. J. Vestli, "FUN: optimization of fuzzy rule based systems using neural networks," in *IEEE International Conference on Neural Networks*, San Francisco, CA, USA, 1993, pp. 312–316.

[5] S. Osowski, L. Linh, and K. Brudzewski, "Neuro-Fuzzy TSK Network for Calibration of Semiconductor Sensor Array for Gas Measurements," *IEEE Transactions on Instrumentation and Measurement*, vol. 53, no. 3, pp. 630–637, Jun. 2004.

[6] S. M. Odeh, "USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) ALGORITHM FOR AUTOMATIC DIAGNOSIS OF SKIN CANCER," p. 8, 2010.

[7] C. Loganathan and K. V. Girija, "Cancer Classification using Adaptive Neuro Fuzzy Inference System with Runge Kutta Learning," *International Journal of Computer Applications*, vol. 79, no. 4, pp. 46–50, Oct. 2013.

[8] A. Atashi, N. Nazeri, E. Abbasi, S. Dorri, and M. Alijani-Z, "Breast Cancer Risk Assessment Using adaptive neuro-fuzzy inference system (ANFIS) and Subtractive Clustering Algorithm," *Multidisciplinary Cancer Investigation*, vol. 1, no. 2, pp. 20–26, Mar. 2017.

[9] S. Mishra, M. Prakash, A. M. Hafsa, and G. Anchana, "Anfis to Detect Brain Tumor Using MRI," *International Journal of Engineering*, p. 6.

[10] S. Alby, "A prediction model for type 2 diabetes using adaptive neuro-fuzzy interface system," *Biomed Res*, p. 6, 2018.

[11] Kavitha, "Adaptive Neuro-Fuzzy Inference System Approach for the Automatic Screening of Diabetic Retinopathy in Fundus Images," *Journal of Computer Science*, vol. 7, no. 7, pp. 1020–1026, Jul. 2011.

[12] M.-L. Huang, H.-Y. Chen, and J.-J. Huang, "Glaucoma detection using adaptive neuro-fuzzy inference system," *Expert Systems with Applications*, vol. 32, no. 2, pp. 458–468, Feb. 2007.

[13] Sri Kusumadewi and Sri Hartati, *Neuro-Fuzzy Integrasi Sistem Fuzzy & Jaringan Syaraf Tiruan*, 2nd ed. Graha Ilmu, 2010.

[14] —J. S. R. Jang, C. T. Sun, and E. Mizutani, "Neuro-Fuzzy and Soft Computing—A Computational Approach to Learning and Machine Intelligence," *IEEE TRANSACTIONS ON AUTOMATIC CONTROL*, vol. VOL. 42, 1997.

[15] Jyh-Shing Roger Jang, Chuen-Tsai Sun, and Eiji Mizutani, *Neuro-Fuzzy and Soft Computing A Computational Approach to Learning and Machine Intelligence*. Prenctice-Hall,Inc, 1997.

[16] Z. Yang, Y. Wang, and G. Ouyang, "Adaptive Neuro-Fuzzy Inference System for Classification of Background EEG Signals from ESES Patients and Controls," *The Scientific World Journal*, vol. 2014, pp. 1–8, 2014.

[17] A. Das and M. Bhattacharya, "Computerized Decision Support System for Mass Identification in Breast Using Digital Mammogram: A Study on GA-Based Neuro-Fuzzy Approaches," in *Software Tools and Algorithms for Biological Systems*, vol. 696, H. R. Arabnia and Q.-N. Tran, Eds. New York, NY: Springer New York, 2011, pp. 523–533.

[18] M. S. Hosseini and M. Zekri, "Review of Medical Image Classification using the Adaptive Neuro-Fuzzy Inference System," vol. 2, no. 1, p. 12, 2012.

[19] S. Kar and D. D. Majumder, "A mathematical theory of shape and neuro-fuzzy methodology-based diagnostic analysis: a comparative study on early detection and treatment planning of brain cancer," *International Journal of Clinical Oncology*, vol. 22, no. 4, pp. 667–681, Aug. 2017.

[20] R. Arun, "AN INNOVATIVE METHOD FOR MR BRAIN IMAGE CLASSIFICATION CORROBORATED ON ANFIS SYSTEM," *International Journal of Computer Application*, vol. 3, no. 3, p. 13, 2013.

[21] D. Jude Hemanth'. C.Kezi Selva Vijila" and J.Anith, "Applicationof Neuro-Fuzzy Model for MR Brain Tumor image Classification," *Biomedical Soft Computing And Human Science*, vol. 16, no. 1, pp. 95–102, 2011.

[22] M. Sharma and D. S. Mukharjee, "Artificial Neural Network Fuzzy Inference System (ANFIS) For Brain Tumor Detection," p. 5.

[23] A. Renjith, P. Manjula, and P. Mohan Kumar, "Brain tumour classification and abnormality detection using neuro-fuzzy technique and Otsu thresholding," *Journal of Medical Engineering & Technology*, vol. 39, no. 8, pp. 498–507, Nov. 2015.

[24] M. L. P. Bhaiya, "Classification of MRI Brain Images Using Neuro Fuzzy Model," *International Journal of Engineering Inventions*, vol. 1, no. 4, p. PP 27-31, Sep. 2012.

[25] Azimeh N.V. Dehkordi, Alireza Kamali-Asl, Ning Wen, Tom Mikkelsen, Indrin J. Chetty, and Hassan Bagher-Ebadian, "DCE-MRI prediction of survival time for patients with glioblastoma multiforme: using an adaptive neuro-fuzzy-based model and nested model selection technique," *NMR in Biomedicine*, 2017.

[26] N. Periyasamy, "Detection and Classification of Brain Tumor Images Using Back Propagation Fuzzy Neural Network," vol. 3, p. 8, 2015.

[27] A. Selvapandian and K. Manivannan, "Fusion based Glioma brain tumor detection and segmentation using ANFIS classification," *Computer Methods and Programs in Biomedicine*, vol. 166, pp. 33–38, Nov. 2018.

[28] R. El Hamdi, M. Njah, and M. Chtourou, "An evolutionary neuro-fuzzy approach to breast cancer diagnosis," *Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics*, pp. 142–146, 2010.

[29] M. L. Huang, Y. H. Hung, W. M. Lee, R. K. Li, and T. H. Wang, "Usage of case-based reasoning, neural network and adaptive neuro-fuzzy inference system classification techniques in breast cancer dataset

classification diagnosis," *Journal of Medical Systems*, vol. 36, no. 2, pp. 407–414, 2012.
[30] M. Ashraf, L. Kim, and H. Xu, "Information Gain and adaptive neuro-Fuzzy Inference System for breast cancer diagnoses," *Proceeding - 5th International Conference on Computer Sciences and Convergence Information Technology, ICCIT 2010*, pp. 911–915, 2010.
[31] A. Atashi, N. Nazeri, E. Abbasi, S. Dorri, and M. Alijani-Z, "Breast Cancer Risk Assessment Using adaptive neuro-fuzzy inference system (ANFIS) and Subtractive Clustering Algorithm," *Multidisciplinary Cancer Investigation*, vol. 1, no. 2, pp. 20–26, 2017.
[32] M. Elloumi, M. Krid, and D. S. Masmoudi, "A self-constructing neuro-fuzzy classifier for breast cancer diagnosis using swarm intelligence," pp. 1–6, 2016.
[33] M. Liang and W. Ahmad, "Breast Cancer Intelligent Diagnosis based on Subtractive Clustering Adaptive Neural Fuzzy Inference System and Information Gain," *2017 International Conference on Computer Systems, Electronics and Control (ICCSEC)*, no. x, pp. 152–156, 2017.
[34] Z. Xiao, M. Adel, and S. Bourennane, "Bayesian method with spatial constraint for retinal vessel segmentation," *Computational and Mathematical Methods in Medicine*, vol. 2013, 2013.
[35] D. Siva, S. Raja, S. Vasuki, and D. Rajesh Kumar, "Performance Analysis of Retinal Image Blood Vessel Segmentation," *Advanced Computing: An International Journal (ACIJ)*, vol. 53, no. 2, pp. 17–23, 2014.
[36] N. B. Prakash and D. Selvathi, "Segmentation of retinal blood vessels in colour fundus images using ANFIS classifier," *International Journal of Biomedical Engineering and Technology*, vol. 24, no. 4, p. 338, 2017.
[37] T. R. Borah, K. K. Sarma, and P. H. Talukdar, "Retina recognition system using adaptive neuro fuzzy inference system," *IEEE International Conference on Computer Communication and Control, IC4 2015*, no. July, 2016.
[38] Jyh-Shing Roger Jang and Chuen-Tsai Sun, "Neuro-Fuzzy Modeling And Control," *Proceedings Of IEEE*, vol. 83, 1995.
[39] M. Subhi Al-Batah, N. A. Mat Isa, M. F. Klaib, and M. A. Al-Betar, "Multiple adaptive neuro-fuzzy inference system with automatic features extraction algorithm for cervical cancer recognition," *Computational and Mathematical Methods in Medicine*, vol. 2014, 2014.
[40] W. Ahmad and A. Ahmad, "Thyroid Diseases Forecasting Using a Hybrid Decision Support System Based on ANFIS , k-NN and Information Gain Method," no. January, 2017.
[41] N. Soumya and N. Pp, "Classification Of Kidney Disorders From Ultrasound Images Using Adaptive Neuro-Fuzzy Inference System," no. 3, pp. 298–305, 2015.