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A CRITICAL ANALYSIS OF DYNAMIC INVESTIGATION BASED ON REASONING TECHNIQUES USING AI FRAMEWORK

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ABSTRACT

Among the metrics used to analyse the results of the experiments are precision, recall, F-measure, ROC, accuracy, and kappa. In this study, these metrics' values must be close to 100 in order to accurately represent classification performance. The rapid development of technology and online life has brought about significant changes in how people communicate. Since handling their enormous amount of collected data is a major factor in interpersonal corporations' effectiveness, all of them are constantly looking for new developments in artificial intelligence as well as ways to create more advanced ones. Understanding the many varieties of human reasoning is a key goal for artificial intelligence. A framework called legitimate reasoning places additional requirements on artificial intelligence techniques. Above all, a computer programme that analyses legal issues must unquestionably identify questions it is competent to answer and questions on which human attorneys could truly argue either side. Software for analysing legal issues should also have the option of using both general legal principles and decisions made in previous instances, as well as the ability of working with specific concepts that are only loosely defined and subject to changes in meaning. Beyond the realm of law, each of these criteria has more extensive applications in artificial intelligence.

Keywords: Artificial Intelligence, Data Mining, Reasoning techniques, Technology, Trouble Shooting.

1. INTRODUCTION

The phrase "intelligent" refers to all living things, including humans, animals, and other species found in the natural world. But more recent developments have expanded this term to include the non-living artificial world and defined artificial intelligence as a whole, which presents various problems, such as whether robots really can think. Can machines have consciousness? Can they study, think, and act independently? Do they have their own intelligence? These problems raise a new dimension of intelligent machines, namely a set of Artificial Intelligence, a phrase John McCarthy proposed at the Dartmouth Conference, and a set of Multiple Intelligence, a theory by Howard Gardner. Giving each concept a detailed description will give a general idea of the concept before moving on to the blending of the two. A human intellectual competence must include a set of problem-solving skills that enable the individual to resolve real problems or difficulties that he or she encounters and, when appropriate, to create an effective product. It must also include the potential for finding or creating problems, which will lay the foundation for the acquisition of new knowledge. (1993 Gardner) According to Gardner's definition, any living being with intelligence is capable of solving issues that are presented to it or it through which a new experience is laid out. The Theory of Multiple Intelligences provides a more comprehensive understanding of the term "intelligent." So, Gardener defined multiple intelligences and listed nine different categories of intelligence in his work "Frames of Mind - The Theory of Multiple Intelligence" from 2011. He claims that every person possesses multiple intelligences, with some being more developed than others. For instance, a musician is not necessarily strong at logical reasoning, and a sportsperson cannot be good at music. The intellect was not randomly chosen out of a hat.

1.1. Intelligence

One definition of intelligence is the capacity for effective knowledge acquisition, retrieval, and application. This applies to both broad and specific forms of information. Memorization, recall, and emotional expression are also part of this category:

- Judgment and decision making,
- common sense,
- Using intuition to make action choices about future events, problem solving utilising creativity, and knowledge by experience and set of beliefs, and so on are all crucial components of human intelligence.

- Reasoning that stands up to scrutiny, a focus on the end result, a strategic mind-set.

The human mind is capable, but it is limited in several ways. Compared to computers, humans are more prone to mental errors, have smaller learning bases, and process material in a linear, time-consuming fashion in their minds. Therefore, the relevance of intelligence is not the data-processing capacity of the human brain but rather the ability of humans to demonstrate intelligence through effective communication and learning.

Humans can acquire knowledge through participation and then demonstrate, by sharing what they have learned with others. Human intelligence is traditionally viewed in psychology as a set of skills and abilities in the realm of the mind.

Learning, reasoning, understanding, creativity, and intuition are currently the primary focus areas in AI research. International research efforts are under way with the aim of developing PCs with the aforementioned features, and these efforts have been successful to some extent.

1.1.1. Methods of Using Intelligence

Uses of intelligence methods could include:

- The use of AI and database technology to collect and organise human expertise, as well as to develop and expand an existing body of information.
- Expert systems, case-based reasoning, and fuzzy logic can all be used to help capture this "tacit knowledge."
- Data mining and neural networks for knowledge discovery, or uncovering previously unknown relationships among large datasets.
- Using evolutionary algorithms to provide answers to really difficult situations
- Utilizing AI bots to carry out mundane responsibilities automatically.

1.1.2. Systems with extensive expert knowledge:

- Capture a person's tacit knowledge in a narrow area of their competence.
- Encourage highly organised deliberation
- Create a model of human knowledge in the form of a database of rules.
- Function by using a collection of if-then rules gleaned from human specialists.
- It's best to employ an inference engine to go through the data. The forward chaining inference method involves the inference engine looking through a knowledge base for an answer, based on input from the user. As the name implies, backward chaining is a process where the computer starts with a hypothesis and then queries the user to verify or refute the theory.
- Knowledge engineers, who turn expertise into rules, and human experts who define the knowledge base are both needed.

1.1.3. CBR (case-based reasoning):

- Keeps records (descriptions of past events) in a database for subsequent review.
- Identifies solutions by looking for previously solved instances that are comparable to the current one.
- Count on the contributions of users to grow and improve over time.

1.2. Application of reasoning

There are various applications that need for deductive reasoning to be performed. When developing robots, it is important to prioritise tasks so that one objective is met before another in order to meet various deadlines. When developing medical diagnosis systems, this is done by attempting to determine the time at which the virus infected the blood system; when developing circuit debugging programmes, it is necessary to reason about the period of time over which the charge in the capacitor increases. In the field of natural language processing, one of the primary concerns of researchers is the extraction and capture of information about sentences' tenses and times. This information is essential to possess in order to be able to respond appropriately to questions regarding the phrases at a later time. Even in fields that at first glance appear to be unaffected by the passage of time, such as mathematical theorem proving, the meta-level thinking that determines how far along a line of proof one should proceed is influenced by the passage of time.

The ability to reason based on temporal information demands a variety of distinct skills. The ability to handle dependencies among various temporal data, the ability to handle incomplete temporal data, the ability to determine the period of validity of data values, the ability to handle real and apparent contradictions, and the ability to recognise incorrect data are some examples of these abilities. Mechanisms for reasoning about temporal structures are concerned with the handling of temporal relations based on the properties of the underlying temporal domain. These mechanisms do not make any assumptions about the kinds of things that can be said to hold over points or intervals of time. Rather, they focus on the handling of temporal relations based on the properties of the underlying temporal domain. Because of this, temporal relations can sometimes be viewed as placing limits on time-dependent entities.

Temporal database management systems, also known as TDBMSs, offer an environment that is well-suited to the purposes of representing, managing, and accessing temporal data. The ability of TDBMS to deliver a vast quantity of accurately represented temporal data is necessary for the practise of temporal thinking. In addition, in order for TDMBSs to be able to meet the needs of temporal reasoning, they must provide additional processes such as reasoning about temporal structures, derivation from partial information, and dynamic changing of inferences while the system is being updated.

The manipulation of constraints is required for any kind of reasoning involving temporal structures. Constructs that allow for the dynamic specification and manipulation of constraints are provided by rule systems. In addition, temporal logics enable one to model both temporally definite statements, the truth value of which is unaffected by the time at which the statements are evaluated, and temporally indefinite statements, also known as relative statements, the truth value of which is affected by the time at which the statements are evaluated. A rule-based modelling approach is an efficient way to model dependencies of this kind. Temporal logics form a framework for temporal query languages. A query language that may be acted upon by rules can be developed with the use of a temporal logic if the evaluation of the logic is dependent on the constraints.

2. THERMAL-AWARE ROUTING APPLICATIONS

Basically, three thermal-aware routing algorithms—the least temperature routing (LTR) protocol, the adaptive least temperature routing (ALTR) protocol, and the thermal-aware routing algorithm—were presented to prevent heat generation. We introduce these three thermal-aware routing techniques in this section.

2.1. Thermally Aware routing algorithm (TARA)

To prevent causing harm to adjacent body tissues, the temperature rise must be considered when biomedical sensors are implanted into human bodies. Additionally, the in vivo sensors need to be recharged by IR radiation when their batteries run out. However, the sensors' temperature rise is also a result of this IR radiation. As a result, it is preferable to limit the number of times sensor batteries need to be recharged by maximising battery life.

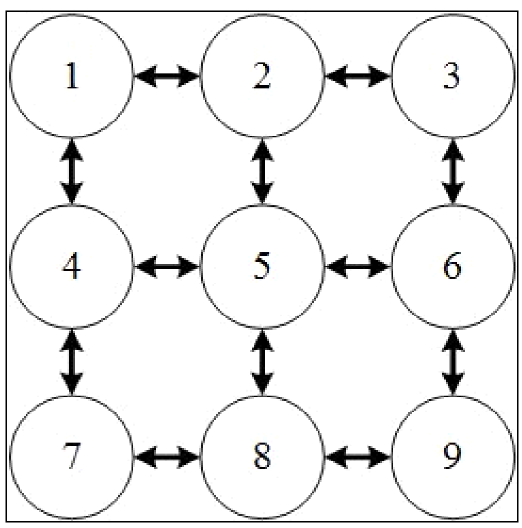

Figure 1: Image of TARA

Figure 1's thermal-aware routing algorithm (TARA) is intended to address these restrictions. Hot spots are initially defined by TARA as regions with particularly high temperatures in which sensor nodes are concentrated for data communications. TARA tries to build a different route to detour around the hot places utilising a withdrawal technique after recognising the hot spots in order not to continue to cause the temperature rise of these locations. In this technique, the current node will send packets back to the sender node when all of the nearby (neighbouring) nodes, save for the sending node, are hot spots. The sender node will then choose an alternative route to avoid the hot spots or it may send it back to its previous node, and so on. TARA considers these nodes as fresh candidates for subsequent routing once the hot areas' temperature has dropped to a certain level. Every node must continuously monitor adjacent node packet counts and calculate communication radiation and power consumption to determine the current temperature of the neighbours in order to carry out TARA effectively. Hot places that are hotter than a certain minimum temperature must be monitored by nearby sensors, and they must then be avoided throughout routing until the temperature is normalised.

2.2. Least temperature routing (LTR)

The least temperature routing (LTR) protocol, which is similar to TARA, is intended to avoid creating routes through hot places in order to maintain a low temperature in certain in vivo sensor nodes. LTR, in contrast to TARA, always selects nearby nodes with the lowest temperature for its routing. Therefore, current nodes automatically send the packets to the coolest neighbours and hunt for the destination unless they are intended to be transmitted to a neighbouring node that is the packets' destination. Additionally, LTR makes use of packet discarding in order to preserve network capacity. Every hop a packet makes while wandering through a network keeps track of its hop count. If the hop count is more than a minimum set by the network, called MAX HOPS, the current sensor node will discard the packet from the network. Additionally, packets that are lost in a network can keep note of the sensor nodes they have most recently gone through in a table in order to prevent endlessly looping the same route. In order to avoid using the same route, the current node will send the packets to the node with the second-lowest temperature if the node with the coolest neighbour, where they would be forwarded, is not already on the table. Thus, an endless cycle over the same route is prevented. Figure 2 is an illustration of LTR, which always selects nodes with the lowest temperature.

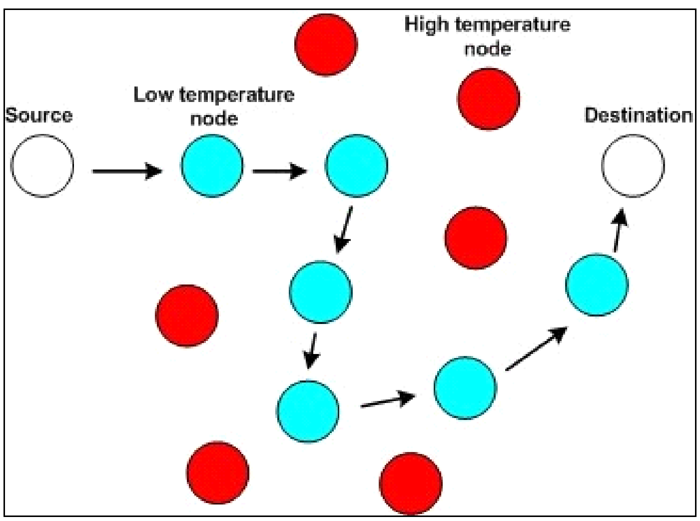

Figure 2: Image of LTR

2.3. Adaptive least temperature routing (ALTR)

The adaptive least temperature routing (ALTR) protocol is a variation of the LTR protocol. When the value of the hop count exceeds a minimal hop count, called MAX HOPS ADAPTIVE, ALTR, like LTR, uses the shortest hop-routing (SHR) protocol as an alternate protocol to get the packets to their destination as quickly as possible. This is one difference between LTR and ALTR. Since some network topologies, such a ring topology, need packet sequences to always track the same path and temperature of sensor nodes on specific paths, ALTR can adapt to specific topologies and, with the use of a proactive delay mechanism, the scheme can scale up quickly. When a neighbouring node sends a packet and there are only two possible routes but both of them have relatively high temperatures, the current node can wait a unit of time before sending the message to the cooler neighbour in order to lower their temperature. Despite a little increase in packet latency, networks' average temperature may drop. Figure 2 shows an example of ALTR, which basically selects nodes with the lowest temperature up until packets reach the MAX HOPS ADAPTIVE hop count threshold. When the threshold is exceeded, packets use shortest hop routing to select nodes that can send them to their destination with the fewest number of hops (SHR).

3. THE PROGRESSION OF MENTAL DEVELOPMENT

In his book "Five Minds for the Future," American psychologist Howard Gardner established five mental subtypes: the educated mind, the integrating mind, the establishing mind, the reverent mind, and the principled mind.

- **The disciplined mind:** This mind develops before adolescence and lasts throughout one's lifetime. This mentality is used in a variety of occupations, including law, administration, medicine, finance, and other scholarly subjects like mathematics, history, physics, and the arts. A person's intellect develops steadily as they gain experience in a certain field; they may already be experts in their field and continue to be so on the job or they may add more disciplinary or interdisciplinary knowledge to their skill set.
- **The Synthesizing Mind:** This mind begins to form in infancy, and under the best conditions, it develops into something even more strategic as it continues to gather new information that must be arranged and processed. This mentality is concerned with drawing information from the available data or choosing some important information from the vast volume of data. They also arrange the information so that it is helpful to both themselves and other people. On the professional front, they recognise the newly available skill or information and then integrate them into your own base of knowledge as well as your professional career. This sort of mind is good at creating assignments and giving competent exams.
- **The Creating Mind:** This sort of mind thinks outside the box and tries to pose a new topic, tends to offer new solutions, tries to configure the present fashion work, and brings together multiple disciplines to create solutions that are beyond imagination. When faced with difficult problems, this mind typically develops a strong personality that continues until mastery of the challenge is not accomplished. This brain thinks outside the box and suggests fresh ideas for procedures and goods. Additionally, they are active in creating the organization's new vision and mission.
- **The Respectful Mind:** The mind requires a nurturing environment from birth and should continue in places like school and the workplace. Others with this mentality react empathetically, think constructively, and behave politely around people who think differently than they do as well as within groups. They make an effort to comprehend other individuals and collaborate with those who are distinct and unusual. They go beyond mere tolerance and political correctness. These people tend to be forgiving and have a strong ability to stay grounded, especially while dealing with those who are at the operational level of the business. A person tries to appear to have a respectful mind-set when they act or demonstrate pure patience without making any effort to interact with or get along with others.
- **The ethical mind:** It is one that strictly abides by the law and works hard to uphold moral principles in both their personal and professional lives. Even in periods of sudden, unanticipated change, people try to find their professions while still adhering to their essential principles. People with these mentalities frequently hold the greatest positions at their places of employment, with maturity playing a significant role in harmony with ethics. It looks forward to the time when someone may naturally and broadly consider his role as a member of society and a human being, and then behave morally based on his moral character. People who preach virtue and responsibility but fail to put it into practise in their own behaviour, who portray ethics in a limited setting but fail to apply it in a bigger one, are the kind of people who pretend to have an ethical mentality.

4. LITERATURE REVIEW

Shridhar Marri (2018) outlined how artificial super intelligence and emotional intelligence can coexist in the same space and at the same time. He goes on to explain that although machines can complete tasks considerably more quickly than people, they still require human direction by being given tasks to complete. This combination will undoubtedly become a powerful force for human advancement. Additionally, he claims that emotional intelligence is lacking in super intelligence, making it harder for humans and artificial super intelligence to relate to one another naturally. In this case, having emotional intelligence in artificial super intelligence would be a major victory for humans. If machines do eventually acquire an emotional repertoire similar to that of humans, it should alter how the modern world looks. Computers are much more efficient than humans at moving things. A person can be selected from a crowd of thousands of people using face recognition software at this time, and complex computations only require a small portion of that time. However, this does not imply that in a society populated by humanistic super intelligences, mankind has nothing worthwhile to offer. No matter how intelligent the machine is, it still needs instructions on what to do. Even the best face recognition software is useless if someone doesn't say, "Find this guy."

In his paper, **Florian Berlinger (2017)** "The Intelligence and Artificial Intelligence Gap Intelligence "argued that the pros and cons of human decision-making and performance. As artificial intelligence research develops, it is important to comprehend computer algorithms. When recreating collective behaviours with artificial intelligence, even local decision-making is crucial intelligence. The most crucial objective is to learn how to make more thorough observations and data which is significant must be retrieved more consistently before reaching the wise choice by the robotic apparatus. Although it is challenging to incorporate such a large database into a tiny space autonomous machine Instead of using the data that is currently available, becoming taught in the real world another enormous task. We can observe animal swarms to learn about collective behaviours. Each makes plans to duplicate group behaviours in line with needs for artificial intelligence knowing how natural decision-making works. Observations of the local environment help to create the choice of options. We want to learn how to make more thorough observations, a how to more reliably filter prenatal information and how to be more successful intelligent system choices for robots. Looking at well-constrained information is one thing on a big mainframe machine. It takes quite another skill to manoeuvre in a muddy area universe where a tiny autonomous golem embodies intelligence being capable of intelligence. Learning in a complex environment is much more difficult than receiving instruction from a textbooka predetermined collection of data.

Egor Dezhic (2017) made a distinction between synthetic intelligence and natural intelligence. Here Natural intelligence is the knowledge that humans possess. He explained that using the tremendous speed Millions of tasks can be completed in the same amount of time that it takes a human to complete one job. Additionally, artificial intelligence can be used at any time and is not biased even if the task is carried out multiple times, a given time at the same precision. However, human intelligence is superior to artificial intelligence in terms of consumption even after using giga watts of energy, the AI can still only carry out a limited number of tasks. To Make AI multi-tasking; it might take years; no need for humans to be created. Our Future typically involves AI and the brain. For instance, Open AI just published a few a method that enables an AI system's manager to communicate goals to the system. In addition, a lot of direction of the analysis is toward brain-machine interfaces. If we can fully resolve the difficulties. The interdependence of humans and robots seems to be quite beneficial for jobs.

Sebastian Ulbert (2017) wrote an article on his website titled "the distinction between synthetic and artificial general intelligence, super intelligence, and intelligence "the three are, it was said in terms of their behavioural habits, they are singularly distinct. He talked about Artificial. The ability of a computer system to mimic human cognitive functions is intelligence. Artificial General Intelligence and Super Intelligence are more advanced ways of solving issues and learning or with a slight variation, general intelligence and intelligence in one are similar to one another task entirely in contrast to super intelligence, as Nick Bostrom claimed: "An intellect that is much more intelligent than the brightest humans in almost every area, including scientific creativity, social skills and broad knowledge.

Beyond AI: Multi-Intelligence (MI) Combining Natural and Artificial Intelligences in Hybrid Beings and Systems by **Stephen Fox (2017)** includes a detailed discussion on Natural and Artificial Intelligence. According to him, human beings have a strong belief in intelligence, and all knowledge created by humans is improved upon by any intellect that already exists. The author thinks that people view it as a fairly straightforward procedure rather than an emerging technology that could lead to hybrid creatures or systems with multiple intelligences. He referred to it as having theoretical underpinnings that can be summed up as Multi-Intelligence situated within the philosophy of Science, Post-Anthropocentric which states about the inclusion of Different Kinds of Intelligences, Organists, and finally as Emergentist, which frames how people talk about technology as having a significant influence on their behaviour. There are many basic flaws in the author's structuring of his fundamental and in-depth study of computer science (AI). The debate of AI is first only theoretical, which restricts its capacity to address the intricacies of action. Second, there is a partisan view of intelligence that elevates human intelligence—as well as intelligence generated by individuals—above all other intelligences. The post-anthropocentric analysis of intelligence consequently doesn't get enough attention. Third, discussions of AI frequently employ mechanistic theory.

Ryan Sheffer (2016) discusses the Singularity. Singularity refers to computer software with artificial general intelligence that is upgradeable, which in turn refers to translating the computational capability of the human brain to a computer. He also compared the human brain to technology concepts like synapses and neurons for storage. A normal human brain is thought to have 100 billion neurons coupled by up to 1000 trillion synapses, which is equivalent to a processor that operates at 1 terabit per second and has a petabyte of memory. Like the human brain, artificial intelligence requires information consumption. According to our scientific understanding of the brain, a collection of synapses and neurons authenticate all human intelligence. Consider a vegetative cell to be "a notion," "a plan," or "an inspiration," such as the idea of "red" or "truck." In contrast, an association could be a synapse or conjunction between neurons. The ability to link neurons is what it is. In your mind, a conjunction would link the words "red," "truck," and "fire fighter," so that you would immediately recognise a particular red truck as a fire engine. By the age of seven, a person's brain should have 100 X 10 rise to 10 neurons with one quadrillion connections. However, human intelligence extends beyond mere data storage (neurons) and memory (synapses); you may also need to be able to absorb data. A man-made intelligence would therefore also enjoy using all the senses that a person has available to them for information gathering. This could be the moment you realise we are far further away from the singularity than some people would have us believe.

5. RESEARCH METHODOLOGY

The framework may be broken down into four discrete phases, and during each step, a significant amount of testing takes place. In order to demonstrate that the proposed models always produce consistent results, it is necessary to use the same experimental setup for each of the four phases.

Phase 1: It comprises of a number of related operations, including data transformation, 10-fold cross validation (CV), format translation, and categorization. A set of input data is mapped to a group of appropriate output data by the feed-forward ANN model known as MLP.

Phase 2: This phase introduces a novel MVR and classification technique for missing data handling based on software agents. To deal with missing data, a new imputation and classification model has been created categorization, 10 fold CV, MVR, and pre-processing

Phase 3: A new classification model based on FS has been introduced in this phase to enhance the classification procedure. This work suggests combining ACO and GA for the FS process.

Phase 4: A novel method for handling MVs that are present in the dataset is presented in this phase. Here, GA is used to create the best possible collection of MV, while GR is used as the fitness function to gauge the effectiveness of each solution. Predicting the presence of MV in the data is the goal of this step in order to achieve effective classification results.

5.1. Experimental Phase

5.1.1. Details of Data Set

Table 1 contains the data pertaining to the dataset.

Table 1: Description of Dataset

Description	CKD
Number of Instances	400
Number of feature	24
Number of Class	2

The applied CKD dataset contains 400 cases overall with 24 attributes included, according to the table.

5.1.2. Performance Measures

Here is a definition of the set of metrics used to evaluate the performance of the suggested models. Four units make up the confusion matrix: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) (FP).

6. RESULT AND DISCUSSION

Precision, recall, F-measure, ROC, accuracy, and kappa are among the metrics used to analyse the experimental outcomes. In order for these measurements to accurately represent classification performance, their values must be near to 100. The results obtained by several models on the tested CKD dataset were displayed in Table 2 and Fig. 3. According to the table data, the fuzzy neural classifier (FNC) model does not provide effective performance, which is supported by minimum precision values of 95.68, recall values of 95.91, F-Measure values of 98.65, ROC values of 97.79, accuracy values of 97.77, and kappas of 92.89. In comparison to FNC, the RBF Network offered superior classification. However, although achieving precision of 98.82; recall, F-measure, and accuracy are all equal at 98.52; ROC is 98.62; and Kappa is 94.69, it does not demonstrate effective categorization.

Table 2: Proposed approach vs. state-of-the-art CKD Dataset

Classifiers	Precision	Recall	F-Measure	ROC	Accuracy	Kappa
Proposed	99.98	99.89	99.96	99.38	99.92	98.99
FNC	97.68	97.93	98.65	97.79	97.77	92.89
DT	99.82	99.82	99.82	99.72	99.77	99.36
1.R	99.52	99.52	99.52	99.72	99.52	98.83
MLP	99.92	99.82	99.82	99.92	99.77	97.28
RBFNetwork	98.82	98.52	98.52	98.62	98.52	94.69
OlexGA	99.00	99.02	99.02	98.32	99.00	95.55

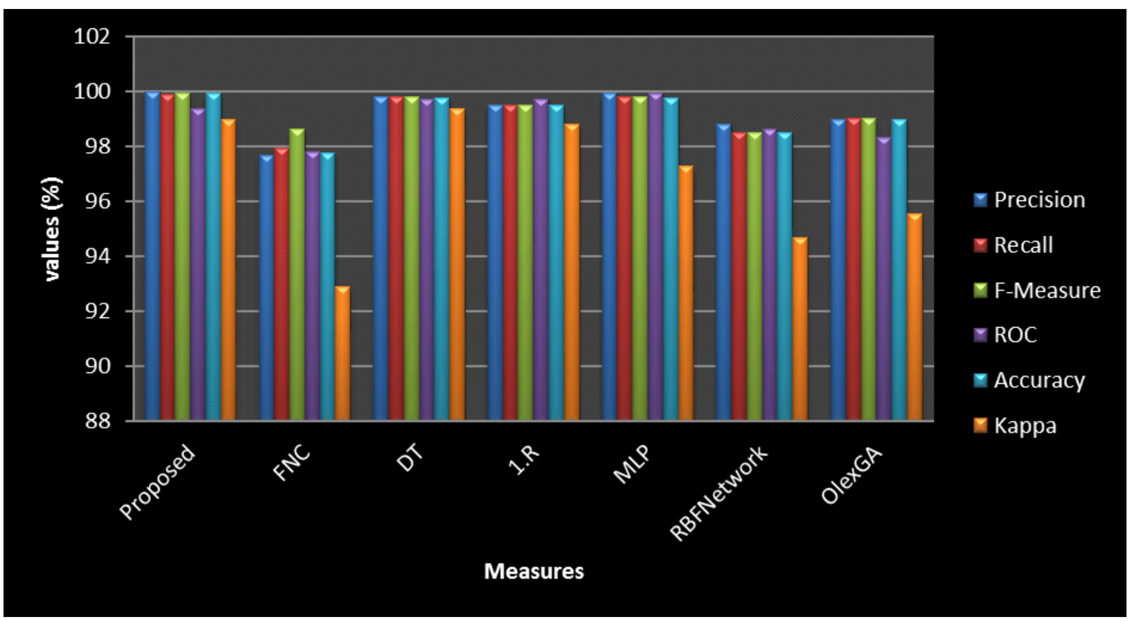

Figure 3: Proposed approach vs. state-of-the-art CKD Dataset

Accordingly, the OlexGA model achieves precision, recall, F-Measure, and accuracy are similar values of 99.02 and ROC of 98.32 and Kappa of 95.55, showing somewhat superior results than FNC and RBF Network. The MLP then exhibits moderate classification with precision of 99.92, recall and F-Measure of comparable value of 99.82, ROC of 99.92, Accuracy of 99.77, and Kappa of 97.28. Secondly, the LR model achieved precision, recall, F-Measure and Accuracy are similar values of 99.52, ROC of 99.72, and Kappa of 98.82, offering reasonable results over other models aside from DT and suggested mode. Meanwhile, the DT model outperformed the suggested technique in terms of outcomes, achieving identical values for accuracy, recall, and F measure of 99.82, ROC of 99.72, Accuracy of 99.77, and Kappa of 99.36. With a precision of 99.99, recall of 99.89, F-Measure of 99.86, ROC of 99.38, Accuracy of 99.92, and Kappa of 98.99, the presented model still provided effective categorization.

6. CONCLUSION

In this study consists of a number of related procedures, including data transformation, 10 fold CV, format conversion, and classification. An efficient MLP with RMSProp model, known as the MLP-R model, is used for the classification problem. The effectiveness of the presented methodology is validated using three benchmark datasets, including those for CKD, hepatitis, and marketing. The simulation results showed that the proposed MLPR model exhibits the best classification performance on applicable datasets under various criteria. Artificial intelligence (AI) issues that mimic fairly typical scenarios that may arise in, say, state or medical determination or the solving of an offence. We referred to these sorts of challenges as "investigation problems"; their goal is to identify the party or parties responsible for a medical or criminal investigation's "miracle." That is, the difficulty is to use the available information to determine which of the possible judgments/suspects (candidates) is most likely to be the cause of the illness/guilty of the violation (which we call the target candidate). Putting things in this light usually leads to more medical tests/police inquiries centred on the probably candidates, which will reveal more information about the current case. We refer to a combination of these issues as a dynamic investigation problem (DIP). Every issue can be solved by applying prior knowledge to the specifics of the situation and using the available data to narrow down the pool of possible solutions to a single viable option.

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