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Data mining based medical intelligent system for chronic kidney disease diagnosis and treatment in the Oromo language

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Abstract: Chronic kidney disease remains a global lethal disease every day, requiring further investigation to tackle the regular heart-breaking death rate admission. In developing countries, the access of a safe infrastructure based on artificial intelligence, the distribution of competent doctors, chronic kidney disease prevention services, and public awareness is severely limited. Medical intelligent systems can address capacity constraint issues in the quest to become the perfect doctor, even exceeding doctors in diagnosis and trappy recommendation. Consequently, the researcher developed a data mining result-based medical intelligent system for chronic kidney disease diagnosis and treatment in Afan Oromo. Hence, the authors used a local dataset gathered using manual and automated knowledge acquisition methods. The preprocessed dataset was modeled and interpreted using different machine learning tools and techniques that converted the resulted rules into a format suitable for the SWI-Prolog tool, command-line software that is primarily used in expert system development. Following that, we have used the SWI-Prolog framework with Java eclipse using Java to prolog connectivity to develop an easy medical intelligent system prototype. The proposed medical intelligent system prototype has been tested for performance and acceptance evaluation and recorded 93.4% and 92.8%, respectively. This is a promising result, proving that the strategy is appealing and useful for diagnosing and treating chronic kidney diseases.

Keywords: *Afan Oromo medical intelligent, Chronic kidney disease, Machine learning, Medical intelligent system*

1. Introduction

Chronic Kidney Disease (CKD) is a disorder in which the kidneys have become damaged and are incapable to filter waste as effectively as normal kidneys as a consequence of waste accumulation in the kidneys over time [1]. Chronic kidney disease is the greatest challenge to the world's health system, especially for developing countries. Where there is a limited amount of research and investigation of the pervasiveness of diseases, the weak and healthy system, the diagnosis and therapy options for the disease are not readily available, especially in sub-Saharan Africa, including Ethiopia. Chronic kidney disease is the main cause of death among people, because the strategy of prevention, detection, diagnosis, and treatment of kidney disease has been weak for many years in Ethiopia [2].

According to reports from the Global, regional, and national burden of chronic kidney disease: a systematic analysis of the Global Burden of Disease Study 2017, This study showed that in the 2015 Global Burden of Disease Project, kidney disease was the 12th most common cause of death, accounting for 1.1 million deaths worldwide. The overall mortality from chronic kidney disease has increased by 31.7% in the past 10 years, making it one of the fastest growing leading causes of death, along with diabetes and dementia [3].

According to the National Kidney Disease Foundation, Chronic Kidney Disease was ranked as the 17th leading cause of loss of life years in the world, with an 18.4% increase since 2005 and the third largest increase of any major cause of death. Accordingly, chronic kidney disease is classified into five stages, from normal (healing) to failure, consequently.

Early detection helps healthcare practitioners provide early treatment, since each stage requires different treatment. Because the disease typically begins as a healing stage and gradually progresses to a failure stage [4].

In Ethiopia, there are not enough specialists and doctors. Therefore, not all patients receive sufficient diagnoses and treatments in time [5]. Also, many people in Ethiopia only realize they have this kidney disease when their kidneys become chronic and affect their lives.

Society thinks that all the symptoms they have are just normal for ever and that they can be okay when they take the pills. It is a traditional arrogance towards the treatment of the disease and the factors which reassure this attitude are the distance to be travelled to the clinic or hospital, which takes a long time to wait for diagnosis and treatment at the hospital. The huge patient dataset collected in hospitals from every patient every day has remains properly unused.

However, when used wisely and technologically, it helps provide effective and efficient chronic kidney disease diagnosis and treatment recommendations when used intelligently with machine learning combined with systems based on the knowledge.

Medical expert systems are the most common form of artificial intelligence used in medical practice. They have medical expertise, usually on a strictly specified mission, and can reason with individual patient data to reach rational conclusions. Expert medical programs hoped to become a perfect physician, assisting or even beating physicians in tasks like dialysis [6].

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Accordingly, Medical intelligent system based on data mining result for chronic kidney disease diagnosis and treatment is proposed to achieve the intended result. This research adds many significant contributions in comparison to earlier work. First it contributes to extends the literature on data mining based medical intelligent systems and document knowledge for future use. Furthermore, the study enhances the diagnosis and treatment of chronic kidney disease by developing user friendly graphical User interface using java and SWI-Prolong combined by java to prolong connectivity techniques. Finally, it highly points to provide the most suitable, efficient, effective, diagnosis and treatment that can be used in medical care center.

Generally, a medical intelligent system is an artificial intelligence system functioning in a specific domain to offer advice and consultation in support of providing effective decisions and enhancing problem-solving capacity in complex situations [7]. The prototype system is designed in Afan Oromo, which is largely spoken in Africa, which makes it very important as a training tool in areas where shortages of skilled human experts are available. It is also useful for a rural area that has a computer system and a scarcity of medical professionals and medication facilities.

The rest of the research is organized as follows: Section two reviews earlier literature on chronic kidney disease, data mining, and knowledge-based systems. The study methodology, data collection procedures, instruments, and techniques are covered in section three. The Section also clarifies machine learning experiments for knowledge acquisition, knowledge modelling, and representation. The section four discusses the use discovered knowledge, components of the proposed knowledge, such as the knowledge base, the inference engine, the user interface, and the knowledge combination facility. Section five of this paper presents the proposed system implementation and discusses how we evaluated the proposed system using test cases and user acceptance testing mechanisms. At the end, section six provides a conclusion and recommendations to show further research directions.

2. Literatures and related works

In recent years many researchers that have been used data mining, knowledge-based systems in order to designed medical intelligence systems for improving healthcare services.

Authors such as Yadollahpour [8] conducted review of predicting techniques for management of to predict the outcome of long-chronic kidney disease, in the study interpreted the discrimination between an artificial neural network and a logistic regression and compared the experiment based on the sensitivity and specificity of logistic regression and a network Artificial Neural Cell in Predicting Kidney Rejection in Ten Kidney Transplant Recipient Training and Validation Data Sets. From the experimental results, both algorithm approaches were complementary and their combined algorithms were used to improve the clinical decision-making process and the prognosis of kidney transplantation. When comparing the prognostic performance of LR with ANN, the ability to predict renal sensitivity was 38% for LR versus 62% for ANN. The ability to predict specificity was 68% for LR compared to 85% for ANN.

Yazawa, et al. [9] gave a cause study approach in predicting kidney disease using classification algorithms such as Naïve Bayes and Support Vector Machine. The study mainly focused on finding the best ranking algorithm based on ranking precision and runtime performance factors. From the experimental result, SVM performs better with almost 76.32% accuracy in the classification process than the Naïve Bayes algorithm.

Zannat et.al. [10] Conduct a study on the Performance Analysis of Chronic Kidney Disease through Machine Learning Approaches to renal dialysis according to the study Survival to kidney dialysis has been a challenging research issue for any investigator. Since the earliest dates of related research, there have been many advances in various related fields. The study is carried out using three data mining techniques (Artificial Neural Networks, Decision Tree and Logical Regression) that are used to obtain knowledge about the interaction between these variables and patient survival. A performance comparison of three data mining techniques was used to extract knowledge in the form of classification rules. The concepts introduced in the study had been applied and tested using data collected at different dialysis sites. Computational results are reported. Finally, ANN is suggested for kidney dialysis for best results with 93.8521% accuracy yield.

The researchers C. Series [11] has applied various machine learning algorithms to a problem in the medical diagnostic domain and analysed their efficiency in predicting the results. The researcher evaluated 12 classification techniques applying them to chronic kidney disease dataset. The decision tree performed better with almost 98.6% accuracy compared to other classifiers such as decision tree, support vector machine (SVM), KNN, artificial, neural network.

Finally, the finding of Senan et al. [12] also concludes that tree-based classifier performs well enough in chronic kidney disease diagnosis which was foundation for this study to build predictive model based on data mining classifier algorithms.

Data mining systems are great at deriving useful knowledge from huge amounts of datasets, but they are not very good enough at converting them into interesting, understandable, and actionable knowledge-based systems. Therefore, research which employs data mining for chronic kidney disease diagnosis merely generates patterns and lacks the use of discovered knowledge. Finally, the researchers advocated for the development of a knowledge base system with adaptability and extensibility features for chronic kidney disease diagnosis and treatment [13].

Consequently, artificial intelligence intends to develop an understanding of human intelligence and build computer programs that are capable of simulating or acting on one or more intelligent behaviors. Intelligent behaviors include cognitive skills like thinking, problem solving, learning, understanding, emotions, consciousness, intuition and creativity, language capacity. Knowledge-Based Systems are an Artificial Intelligence subfield that works on knowledge-bases for effective decision making by imitating the behavior of human experts within a well-defined, narrow domain of knowledge.

The study carried out by Belay et.al [14] in the area of medical diagnosis knowledge-based system has recommended localization concepts in terms of language as a result of multination and nationality support and equality engagement in the country.

Siraj Mohammad [15] has attempted to design an Amharic-based knowledge-based system for the diagnosis and treatment of chronic kidney diseases. Knowledge was acquired through structured and unstructured interviews with experts in the domain and relevant documents using the document analysis method.

The collected knowledge was modelled using the decision tree approach and programmed using the SWI-Prolog tool to form the knowledge-based system. However, the main goal of knowledge-based systems is to encapsulate tacit and explicit knowledge in a particular area and to code the knowledge in a way that it is accessible to novice users. The importance of this knowledge-based system could be an approach for knowledge acquisition

techniques to develop better rule-based reasoning applications, which includes the ability to maintain the patient's history and reuse it for diagnosis and treatment.
The researchers focused only on three stages (1st stage, 2nd stage, and 3A stage) out of the five stages of chronic kidney disease. Therefore, the system is incomplete and not a simple graphical user interface prototype system designed to enhance the non-professional computer user's experience. Nevertheless, it must be comprehensive in order to integrate the remaining stages of kidney disease, such as Stages 4 and 5, to become a complete system.
In other words, the researcher has stated that the method of acquiring knowledge should be improved as there were challenges during gathering knowledge from domain experts.
Similarly, the same author recommends combination of data mining results with knowledge-based systems makes them intelligent, since both are self-learning techniques. The researcher recommends that it is important to apply data mining techniques to extract hidden knowledge, since it is difficult to extract more tacit knowledge through interviews. This hidden knowledge in data mining is known as rules, which could be used for rule-based reasoning system development.
The most widely utilized approach in knowledge-based systems is rule-based reasoning. As a result, condensed representation of general knowledge, naturalness of representation, modularity, and supply of explanations are some of the primary advantages of Rule Based Reasoning systems.
According to the study [16,17], Afan Oromo (Oromo language) is the second most widely spoken language in Africa, with over 55 million speakers, first largely spoken in Ethiopia by more than 36 million peoples, which should be taken into account while designing any societal service system.
As mentioned in study section 2 of this study, combining two or more distinct problem-solving and knowledge-representation methods is a hot topic in AI research. However, no attempt has yet been made to combine data mining with knowledge-based systems to build a rule-based medical intelligent system for chronic kidney disease diagnosis and therapy consultation in the Afan Oromo (Oromo Language).
Therefore, this study proposed a data mining-based medical intelligent system in Afan Oromo for chronic kidney diagnosis and treatment recommendation. The proposed system is supported by a simple java graphical user interface prototype, a local dataset used for analysis and interpreting with machine learning algorithms, and the result is combined with domain expert knowledge to design a medical intelligent system.

3. Methods

A research methodology is an arrangement of conditions for the placement and analysis of data in a way that aims to address the research problem [18]. It includes data collection methodology, data pre-processing sampling techniques, and feature selection techniques, experimentation tools and techniques used in this study.
The research design is generally known as the conceptual framework of the study to be followed in any practical investigation.

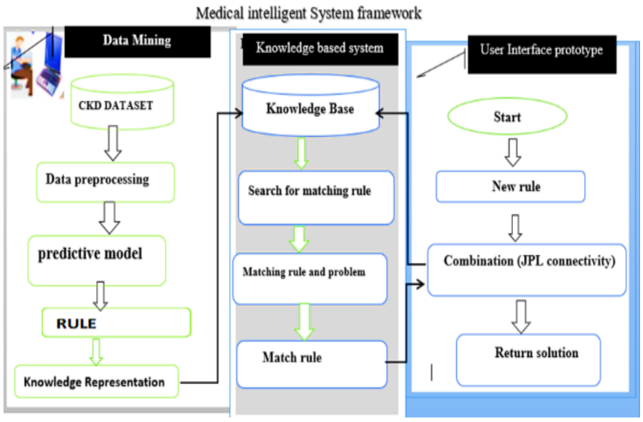

Fig. 1. Framework of the system

3.1. Manual knowledge acquisition techniques

The researcher used mixed method of quantitative and qualitative for data collection procedures. Mixed methods provide a lot of flexibility and can be used with a range of research methodologies, such as observation, to find more information than simply quantitative research can provide. The method also matches how people naturally gather information by integrating quantitative and qualitative data with qualitative data (descriptions and visuals of highlights) to provide a more comprehensive explanation than either technique alone could provide.
The qualitative data used in this study has collected mainly through literature review, interview and document analysis. Researcher has conducted interview with selected domain experts to have better understanding about the disease and its consequences. The researcher has purposively selected six domain experts based on their specialization or field of study, interest to respond and availability. The researcher has reviewed related documents, namely research papers, magazines, theses, and articles and works in the areas of machine learning and chronic kidney disease. The researcher performed different document analysis and observation of hospital work procedures electronically and physical observations.

3.2. Data mining Tools and techniques

The researcher used machine learning tools and techniques to pre-process, analysis and extract knowledge from quantitative dataset collected from the hospital patient cards. To realize the objective of this study, the researcher has used the Knowledge discovery in databases (KDD) process model. Since its most recently used methodology, it provides accessibility to a fully comfortable, easy, and completely supportive method for data understanding, preprocessing, model building, and result evaluation [19].
The dataset was preprocessed using Microsoft Excel and WEKA, followed by the KDD process. Based on previous research, the researcher chose supervised machine learning algorithms such as J48, PART, and JRip classifiers for their power in knowledge representation and ease of interpreting their results to the researcher's potential for data mining experiments [20].
Hence, automatic knowledge was collected using a machine learning classifier algorithm in the form of an if-then-rule format with the help of the Weka Machine learning tool. As the result of knowledge representation, the knowledge is represented in rule-based representation with domain experts consult, since it is easy to construct rule-based reasoning systems. After mining the hidden knowledge from the pre-processed dataset and comparing the performance of classifiers, the researcher combined knowledge acquired from both sides.

The researchers used SWI-PROLOG version 7.6.4, the programming language, to develop a knowledge-based system library. Java eclipse IDE8.0 with JDK 8, and Java to Prolog (JPL) library was employed to combine the knowledge-based system with the GUI prototype. Java eclipse is more portable, faster, easier, and efficient project management, and it offers the best support for the latest Java technology. It can also be installed on any operating system that supports Java [21].

3.3. Evaluation methods

To evaluate the performance of the developed classifier model, the researchers used precision, recall, and F-measure to evaluate the results and accuracy of the data mining model. The calculation formula is given : -

Recall: is an access of correctly classified instances as positive or correct.

$$\text{Recall} = TP/ (FP+FN) \quad (1)$$

Precision: Precision is a statistic for calculating the percentage of positive tuples that are genuinely positive.

$$\text{Precision} = TP/ (TP+FP) \quad (2)$$

Accuracy: Classifier model accuracy is frequently expressed as the ratio of successfully categorized tuples to the total number of occurrences.

$$\text{Accuracy} = (TP+TN)/ (FP+FN+TP+TN) \quad (3)$$

F-measure: This is often calculated as the average value of recall and precision.

$$\text{F-measure} = (2*\text{precision}*\text{recall})/ (\text{precision} + \text{recall}) \quad (4)$$

Where, FN stands for False Negative; FP is for False Positive, TP stands for True Positive, and TN is True Negative.
The researchers evaluated the Knowledge based system using system prototype by preparing test cases and users' acceptance testing questionnaire which helps the researcher to make sure that whether the potential users would like to use the proposed system frequently and whether the proposed systems meet user requirements.

3.4. Data preparation

The quantitative dataset used to conduct this research was collected manually, from the patient history dataset of St. Paulo's Hospital, the second-largest public hospital in Addis Ababa, the capital of Ethiopia. Moreover, by assessing different information about the hospitals, St. Paul's Hospital was selected because there could be a high number of patients with chronic diseases and dialysis treatment is given at the hospital. The hospital launched the kidney transplant center in 2015. It makes the service available and provides an excellent opportunity for researchers and policymakers to conduct program monitoring and evaluation. The total dataset collected for this study consists of 27 descriptive attributes and five solution attributes. Raw data is highly susceptible to irrelevance, redundancy, and noise, which results in low quality results, data preprocessing is critical to improving the quality of the result. Hence, the data preprocessing task has been made as follows:

3.4.1. Handling Missing value

The total dataset collected from the hospital consists of 138 missing values with either categorical or numerical data type. Therefore, the researcher represented the missing values of the dataset with mean and mode as per their respective data types. The redundant value instance dataset has been removed with the help of the Weka machine learning redundancy removal tool to improve data quality.
Finally, the pre-processed dataset consists of patient data classified as stage-1, which is a normal or highly functioning kidney, which means that the patient has no kidney disease but needs to be observed for related disease. The researcher used this class label as ''normal'' for this study. Stage 2 consists of 248 datasets classified as stage 2 or mild. Here the researcher used the class label as "stage 2-mild" in this study. Stage 3, or moderate class, has 257 datasets. Stage 4, or severe CDK, consists of 399 datasets. And the last class, stage 5, or end stage CDK, has 442 datasets, the largest class in the whole class used in this study.

3.4.2. Feature selection

The researchers used information gain ratio and report from previous studies to select the most relevant attributes used in chronic kidney disease stage diagnosis and treatment for the purpose of this study. However, in order to enhance both evidences, the researcher has employed domain expert consultation in feature selection from the dataset. Hence, irrelevant features, namely albumin, appetite, blood glucose random, puss cell and puss cell clumps, pedal epidermal, and bacteria, have been removed as the result of the feature selection techniques.

3.4.3. Data formatting

The dataset used in this study was manually collected from the patient history card. Therefore, it should be converted to softcopy to prepare a machine-readable dataset. The collected dataset is saved in Comma Separated (CSV) format and the latter converted to (.arff) weka file format to enhance accessibility to the weka setup.

3.5. Creating Predictive learning Models

In this experiment, a chronic kidney disease dataset collected from Stephen Paul Hospital patient cards was used. The total dataset is consistent with 1718 instances and 21 attributes were sampled as the result of the preprocessing step that has been used for this model building experiment. The predictive model is built with three machine learning algorithms, namely J48, PART, and JRip. J48 is a tree-based classifier, whereas PART is a rule-based classifier.
In order to evaluate the proposed classifier models and interpret the results obtained from the experiment, the most commonly used tools in machine learning studies, such as WEKA analysis, were employed for knowledge acquisition and analysis in this study. Since it is open source and easy for researchers to accomplish the study, Hence, for the proposed model validation, the performance of the algorithms is evaluated as the accuracy registered by each algorithm in each experiment setup. Thus, the most commonly used decision tree classifier model evaluation method, namely, precision, recall, accuracy, and f-measure, to evaluate the proposed chronic kidney disease prediction models sequentially. First, the dataset is systematically divided into training sets and test sets as follows:
The training set with its respective 34% test sets is used, and the next step is the application of K-fold (k = 10) cross validation on the sampled dataset for model building. Consequently, the best results of each model are compared together, and the one with the highest result is selected as the best learning model. The resultant algorithm is used to extract knowledge for the next experiment.
Finally, the proposed method needs to be evaluated against the

objective to be realistic, applicable, and representative of the organizational problem with the respective solution. To this end, the result of the proposed medical intelligent system prototype has been validated with domain expert judgments carried out by the system evaluator to classify the test cases into correct or incorrect classes. The evaluation is done by comparing the system test results with the physician responses.

Experiment 1: Model Built with J48 classifier Algorithm

In this experiment, we have been used J48 is an open-source Java implementation of the C4.5 algorithm in the WEKA data mining tool, which is used with the default value parameter, 10-fold cross-validation, and the 66 percent split test option. The result is shown in table 1.

Table 1. J48 model experiment

J48 algorithm			
Test option	Precision	Recall	f-measure
66%	97.8%	97.8%	97.8%
10-fold	95.9%	94.8%	95%

Hence, in this experiment, 97.8% of the total dataset is correctly classified, while 3.25% is incorrectly classified when the default 66% split test option is used instead of the 10-fold cross validation test option.

Experiment 2: Model building with PART algorithm

The second experiment in this study has been undertaken with the PART algorithm. Similarly, the same test option that is used with the default value parameter, 10-fold cross-validation, and the 66 percent split test option, has been applied to a similar dataset. The precision, recall and f-measure of the model is shown in table 2:

Table 2. PART model experiment

PART algorithm			
Test option	Precision	Recall	f-measure
66%	97.3%	97.1%	97.1%
10-fold	98.2%	98.1%	98.1%

Experiment 3: The model building with JRIP algorithm.

The third experiment was conducted with the JRIP algorithm with a similar experiment setup to both previous test options, namely the same test option that is used with the default value parameter, 10-fold cross-validation, and the 66 percent split test option. In this experiment, 98.117% of the total datasets were correctly classified, while 1.8% of them were incorrectly classified during the utilization of the 66% split test set option as a test parameter.

Table 3. Models built with JRip

JRIP algorithm			
Test option	Precision	Recall	f-measure
66%	98.3%	98.3%	98.3%
10-fold	98%	98%	98%

The result of 66% percentage split has used as the better result of the algorithm after come up with no dramatic change in result during the parameter adjustment test which was made upon ever outperformed steps in similar test set.

3.6. Comparison of classifier algorithms

The comparisons of the best model are made with precision, recall and f-measure as proposed evaluation method criteria of this study. Hence, the model with the highest precision, recall, and f-measure has been selected as the best learning model of these experiments. To this end, the predicting performance of the best of each of the three modelling techniques on their learning model after being evaluated with their own corresponding parameter set adjustment test is shown in table 4.

Table 4. Result comparison of better model

Algorithms	**Precision**	**Recall**	**F-measure**
J48	97.8%	97.8%	97.8%
PART	98.2%	98.1%	98.1%
JRip	98.3%	**98.3%**	**98.3%**

From table 4, JRip has outperformed the proposed three learning models with 98.3% equal precision, recall, and f-measure respectively. The PART algorithm has performed better with 98.2%, 98.1% and 98.1% precision, recall and f-measure respectively. Besides this, J48 has taken the third place with an equal 97.8% precision, recall, and f-measure respectively.

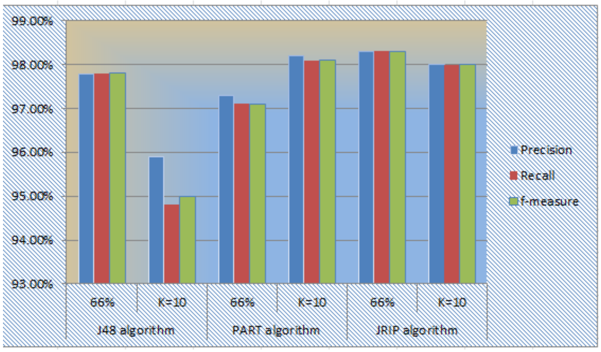

Fig. 2. Model performance comparison

However, we have used Weka default parameter values for two trials in modeling steps. The experiment conducted with 66% showed better results compared to the k-fold cross validation parameter in all experiments. The results obtained in all the experiments are better, but the model built with the JRip algorithm has performed better than the other algorithms. Therefore, the result of the JRip model has reasonable potential for deployment in the next rule-based medical intelligent system development step.

Therefore, one can deduce that the JRip Rule-based learning models perform better in chronic kidney disease diagnosis and treatment than the J48 and PART models. Hence, this study has investigated the JRip Rule-based classifier algorithm could produce more accurate results in chronic kidney disease diagnosis and treatment. Henceforward, in addition to its highest accuracy in predicting the stages of chronic kidney disease, the JRip modelling technique is too simple to understand for individual users who are not domain experts [22]. This is because the products of the models in JRip are given simply as a set of generated rules.

There are some factors which can affect the performance of the models. The use of free data mining tools with limited capability in handling large amounts of datasets and dataset characteristics, for example, can have an impact on algorithm performance in terms of accuracy and elapsed time. The performance of models can decline as the sample size grows, or the performance of the data mining technique can be inconsistent when the sample size is small. As a result, 1718 large enough instances of the data set were utilized to develop learning models in this work, with two different validation experiments performed on free Weka machine learning software. Despite these limits, the model's overall performance has been recorded at 98.3 %.

On the other hand, the dataset collected from the patient history card consists of classes labelled as normal CKD, mild, moderate, severe CKD, and end stage CKD, which is easy for everyone to prepare even with MS excel and MS access and utilize to classify chronic kidney disease stage for further diagnosis and treatment. Therefore, JRip modelling techniques have the realistic capacity to be employed in the medical health care system to enhance medical diagnosis and trappy recommendation systems.

To this end, the result of the JRip machine learning rule-based classifier modelling techniques has been used for the next rule-based intelligent system development experiment.

The rules generated from the JRip base contain five rules for normal stage, four rules for mild, one rule for moderate, one rule for severe CKD, and also one rule for end stage chronic kidney diseases. The result of this experiment can be interpreted as follows: from the sampled CKD dataset used, 85% is predicted as having normal stage chronic kidney disease, while 68% of the dataset is classified as mild stage, and the remaining portion is equally predicted as moderate, severe, and end state.

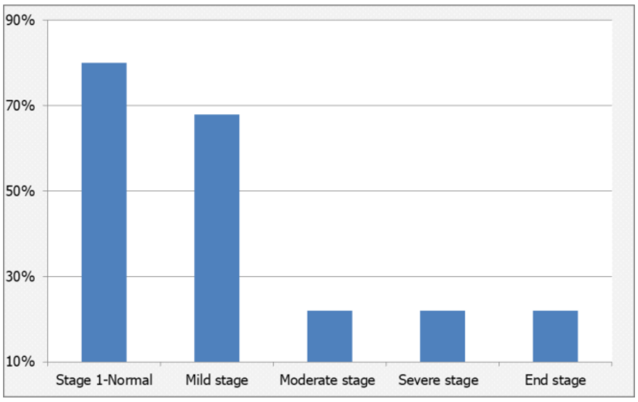

Fig. 3: Result interpretation

CKD classification stage should only be used to stage chronic kidney disease patients. Normal stage is the first stage in this classification, which means that patients with stage are more likely to have the incidence increase progressively as the stage advances when compared to patient without CKD.

According this study, the total number of patients in this first stage is the largest, indicating that they must undergo good follow-up in order for their kidney to continue performing at 90% or above.

Consequently, this finding is critical for slowing the progression of the disease. Because a high proportion of first-stage chronic kidney disease is detected early before it worsens, it is possible to stop it from progressing through treatment.

Furthermore, patients with mid stage CKD is ranked second. However, It is, lower than the normal stage, this stage has a higher population than the other classes. This indicates progress of subsequent stages may continue at this rapid pace if not handled properly.

Similarly, the overall number of patients with moderate, severe, and end-stage chronic renal disease is comparable, despite largely different treatment options. According to the findings, the number of people requiring renal dialysis or transplantation is roughly equal in the moderate and severe stages. This shows that, in addition to poverty and other issues, the disease is a persistent health problem in the country. The outcome is promising in terms of addressing the issue of early diagnosis, which is critical in reducing disease severity and mortality.

4. Use of Discovered knowledge

The main focus in this section is on how to use the knowledge extracted from machine learning for knowledge-based systems. The result of these machine learning algorithms is the foundational development of knowledge-based reasoning systems, which is the family of Artificial Intelligence. Hence, without a knowledge base, there is no intelligence persistence in any artificial intelligent system. Therefore, machine learning is used as the rule generator in the rule-based reasoning system for this study.

After knowledge acquisition is done using a JRip rule induction algorithm, which is performed on the CKD dataset, the rules extracted are validated by a domain expert and represented in the knowledge base system. For this study, we used Weka machine learning tools to construct a predictive model. Finally, we combined the results of the JRip model with a domain expert knowledge and construct knowledge-based system for diagnosing and treating chronic kidney disease.

4.1. Mapping predictive Knowledge into Knowledge base

In this study, the rules generated with the JRip induction algorithm have been employed to develop a medical intelligent system prototype. The algorithm has generated 12 rules which have been proved by domain experts as important knowledge in chronic kidney disease diagnosis and treatment.

Table 5: Sample rule generated from JRip algorithm.

No.	Rules
1	(Sg <= 1.015) and (Scr <= 1.28) => ckd_status=mild (92.0/9.0)
2	(Htn = yes) and (Age <= 54) and (Scr <= 1.35) => ckd_status=mild (24.0/4.0)
3	(Htn = yes) and (Sod >= 138) and (Scr <= 1.6) => ckd_status=mild (32.0/11.0)
4	(Scr >= 1.22) and (Age <= 48) and (Scr <= 1.46) => ckd_status=mild (33.0/10.0)
5	(Scr <= 1.2) and (Sod >= 142) => ckd_status=Normal (129.0/1.0)
6	(Scr <= 1.2) and (Pltc <= 205) => ckd_status=Normal (79.0/2.0)
7	(Scr <= 1.2) and (Hgb >= 13.2) and (Sg <= 1.025) and (Mcv >= 86) => ckd_status=Normal (56.0/2.0)
8	(Scr <= 1.7) and (Pot <= 4.2) and (Chl <= 100.7) and (Mcv >= 94) => ckd_status=Normal (4.0/0.0)
9	(Bun < = 17.8) and (Sod >= 143) => ckd_status=Normal (4.0/1.0)
10	(Scr < = 2.59) = > ckd_status=moderate (451.0/165.0)
11	(Src < = 4.38) = > ckd_status=severe (384.0/91.0)
12	=> ckd_status=ESRD (430.0/49.0)

The JRip algorithm generated the rules in natural language format, which follows: if (condition) then (conclusion). The condition part is made up of attributes and, while the comparison operation is utilized as a bridge to offer a solution in the middle. Two or more conditions are joined by 'and '. After the conditions, the '=>'meaning implies follows. The conclusion part of the rule has the format class='ckd_status', for example ckd_status=severe class=moderate.

To this end, for a chronic kidney disease to be classified as normal, both the antecedent of (Scr = 1.2) and (Pltc = 205) should be true. In other words, if the disease stage is mild (Sg = 1.015) and (Scr = 1.28), This is the general rule format supported by the JRip machine learning algorithm. However, Prolog, the knowledge

base development tool, does not support this IF... THEN format. Prolog works in a completely different format. Therefore, the rules generated by the JRip algorithm must be converted to the format supported by Prolog [23].
Prolog uses the backward chaining method. It starts with a goal and then goes to the facts that can prove the goal as true. Therefore, the result of JRip we found has a different structure, and we have been swapped with the form that can be supported by Prolog programming language during programming as Src <= 1.2 and Pltc <= 205=> ckd_status = normal. Similarly, all the rules generated from JRip need to had converted to the deduction format supported by Prolog, to achieve the general objective of the study.
The goal of chronic kidney disease diagnosis is to determine whether it is normal, mild, moderate, severe, or end-stage renal disease. The assessment result, the final treatment recommendation has been given by the system [24].
The main aim of the study is to use mixed methods of knowledge acquisition to design medical intelligent systems for the diagnosis and treatment of chronic kidney disease. The primary dataset used to conduct this study was collected by a domain expert. Through interviews, literature reviews, observation, and document analysis.

4.2. Treatment knowledge

Treatment is always given after clearly identifying the stage of the disease, therefore follows the same procedures in representation of treatment knowledge into the system. The treatment for all stages of CKD is given as follows, based on the National Kidney Foundation and domain expert consult [25].
Stage 1: Normal or high functioning kidney, but to continue with heal kidney, the following treatment is recommended by physicians.
Manage blood sugar levels if you have diabetes.

- Follow your doctor's advice for lowering blood pressure if you have hypertension.
- Maintain a healthy, balanced diet and right bodyweight.
- Avoid use tobacco and alcoholic.
- Engage in physical activity for 30 minutes a day, at least 5 days a week.

Stage 2: Mild stage: - digestible loss of kidney function over time (GFR 60-89 ml/min) and Treatment will be:

- It's time to develop a relationship with a kidney specialist.
- It's important to address the underlying cause. If you have diabetes, high blood pressure, or heart disease.
- Follow doctor's instructions for managing these conditions.
- It's also critical to eat well, exercise regularly, and keep track of your weight.

Stage 3: kidney disease:
It consists of Stage 3A, which means your kidney is functioning between 45%-59%, and Stage 3B, which means kidney function is between 30%-44%. Hence, the kidneys aren't filtering waste, toxins, or fluids, so they're beginning to accumulate.
The important thing is to manage underlying conditions to help preserve kidney function. This may include:

- To relieve fluid retention,
- Cholesterine-lowering drugs
- Erythropoietin supplements for anemia
- Vitamin D supplements can help with bone deterioration.
- phosphate binders to prevent calcification in the blood vessels
- lower protein diets so your kidneys don't have to work as hard.
- Frequent follow-up visits and tests

Stage 4: Severe chronic kidney disease: moderate-to-severe kidney damage.

- Kidney functioning between 15-29%, so may be building up more waste, toxins, and fluids in your body.
- It's vital to prevent progression to kidney failure.
- Follow up and all about planning dialysis.
- These procedures require careful hospitalization and a lot of time, so it's wise to have a plan at this stage.

Stage 5 -kidney disease (End-stage renal disease)**:** This means that the kidneys are operating at less than 15% of their maximum capacity. When that happens, the kidney build-up waste and toxins becomes life-threatening.

- Hence, life expectancy is only a few months without dialysis.
- Dialysis isn't a cure for kidney disease, but removes waste and fluid from your blood.

4.3. Java interface to prolog connectivity (JPL)

Java Interface to Prolog connectivity is a library using the SWI-Prolog foreign interface and the Java jni (Java Native Interface) interface providing a bidirectional interface between Java and Prolog that can be used to insert Prolog in Java as well as vice versa [26].
The intended medical intelligent system is implemented as modules containing the knowledge base, user interface module, and stage description module. Knowledge base is a collection of rules automatically constructed by integrator application. For this study, the selected classifier has generated a total 12 valid rules about five stages of chronic kidney disease from the End stage kidney failure to the normal heal kidney behaviors.
Rule-1: ckd_status=normal: - Scr <= 1.2) and (Sod >= 142)
Rule-2. Ckd_status = mild: - (Sg <= 1.015) and (Scr <= 1.28).
Rule-3: Ckd_status= moderate: - (Scr < = 2.59)
Rule-4: = Ckd_status=severe: - (Src < = 4.38)
Interface engine is the understanding of the Knowledge Based System which directs the system how it can derive a conclusion by looking for possible solutions from the knowledge base and recommend the best possible solution. Inference engine is responsible for controlling the way knowledge in the knowledge base accessed and communicates the result via user interface to the user.
Since the objective of the proposed Knowledge Based System is to diagnosis and treatment of stage of chronic kidney disease and the Prolog's built-in inference mechanism is backward chaining, the researcher has preferred to use backward inference mechanism which is a goal derive that tries to prove or disprove the goal but the user use data driven.
The rule based medical intelligent system presents a serious of questions to the user using this module. User interface module is designed in a manner to accommodate any changes in the rules and facts. The questions displayed are based on the contents of rule and fact bases. Whenever a change in either of the two appears, the question asked also changes accordingly.

```
? - start
|   does Scr <= 1.2 [yes /no]
|   does Mcv >= 86 [yes /no]
|   does Sg <= 1.025 [yes /no]
|   does Bun <= 17.8 [yes /no]
|   does Bun <= 17.8[yes/no]
```

Following the successful combination of induced knowledge with the knowledge-based system, the rule based medical intelligent system for diagnosis and treatment is built.

5. Proposed System Implementation

The objective of this study is to use the discovered hidden knowledge using machine learning techniques and knowledge-based systems to design data mining result-based medical intelligent system for chronic kidney disease diagnosis and treatment recommendation. A machine learning rule induction algorithm model is used for constructing rule-based systems integrated with domain expert knowledge. These systems are combined systematically to enhance the performance of a designed medical intelligent system for the diagnosis and treatment of chronic kidney disease.

5.1. Graphical user interface prototype

The Graphical user interface is a channel for communication between the system and the end user of the system. The researchers used SWI-prolog programming to develop a medical intelligence system for chronic kidney disease diagnosis and treatment recommendation. However, the command line interface of Prolog is not user-friendly for non-computer professionals. Therefore, the researcher preferred to develop the graphical user interface with Java Eclipse IDE 8.2 supported by JDK 8.0, since it is simple to integrate SWI-prolog with Java api via Java to interface prolog library. Hence, the system works by automatic inter-crossed mutuality that strengthens the system performance in addition to its simplicity.

This graphical user interface was developed based on the model generated by the JRip rule induction algorithm with 21 attributes. The rules used by the researcher to design the graphical user interface prototype for diagnosis of CKD diagnosis and treatment are the 12 diagnosis rules and 5 rules for its treatment.

These rules have been translated into Oromo language (Afan Oromo) for the benefit of Ethiopia's huge Oromo community.

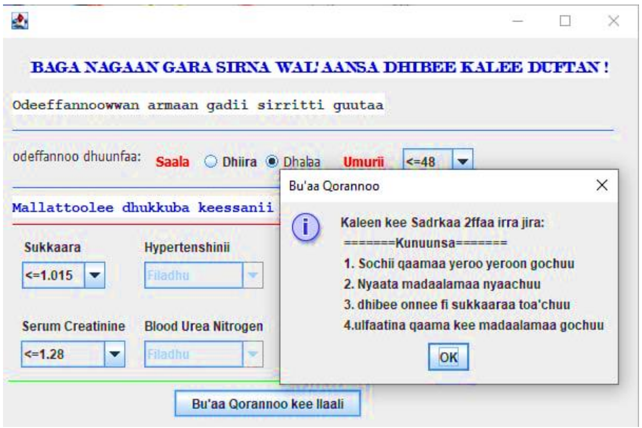

Fig. 4. User Interface Prototype for CKD diagnosis and treatment

The diagnosis process is based on interacting with the user by presenting the user with a series of questions. The system prompts the user by displaying a selection option for questions containing attributes and their values. Hence, when the users respond to the questions, it certainly; the system displays the result (Bu'aa qorannoo) of the CKD diagnosis as Normal stage, Mild CKD, Moderate CKD, Severe CKD, and End Stage CKD.

5.2. Evaluation of the system prototype

In order to assure the medical intelligent system for CKD diagnosis and treatment meets the requirements of its development, the researchers have accessed the system with both the system performance test and user acceptance test methods, which are commonly used by researchers to evaluate the system.

5.2.1. System performance Test

The performance of the system is evaluated by preparing test cases. Most of the time, system performance testing is essentially used to measure the accuracy of the system in relation to the desired solution with certain accuracy. Hence, the confusion matrix is used for comparing the performance of the system with domain experts. Confusion matrix employees, F-measure, Recall and Precision measure how the system is accurate in diagnosis and treatment provision.

To this end, the researcher has used 40 test cases, prepared from a dataset with domain expert consultation, considering different critical situations mentioned by the consultant, such as comorbidity complex. The confusion matrix for system performance tests with domain expert judgment is shown in table-6.

Table 6. confusion matrix for system performance evaluation

Actual Classes	Normal	Mild	Moderate	Severe	ESRD	Total
Normal	7	1	0	0	0	8
Mild	1	7	0	0	0	8
Moderate	0	0	6	0	0	8
Severe ckd	0	0	0	8	0	8
ESRD	0	0	0	0	8	8
Total	7	7	6	8	8	40

The test indicated that out of 40 test cases, 34 were correctly classified and 6 were incorrectly classified. The overall correctly classified accuracy of the medical intelligent system has been recorded as 90% in medical diagnosis and treatment of chronic kidney disease. The result is encouraging to use the medical intelligent system prototype for chronic kidney disease diagnosis and treatment in hospitals, health professionals, health extension workers and an educated family to deliver fast and effective diagnosis and treatment service.

5.2.2. User Acceptance Test

The aim of undertaking user acceptance testing is to make sure how well an integration of prediction model with the knowledge-based system for diagnosis and treatment of chronic kidney disease is performing from the users' point of view so as to make sure that the system is accepted and usable by users.

Five domain experts are selected to test the system by responding to a series of questions. These experts are taken from Stephen Paul hospital, one from the medical ward, three general practitioners and one nurse based on their availability, knowledge and interest. The evaluators assessed a medical intelligent system based on the diagnosis and treatment of CKD by using the following standards adopted from [27].

- Easiness of use and interaction with the system
- Attractiveness of the system
- Efficiency in time
- The importance of the KBS in the domain area
- The accuracy of the system in reaching a decision
- The ability of the system to make the right conclusions and recommendations

The researchers have used user acceptance testing evaluation criteria with rating values as Excellent = 5, Very Good =4, Good = 3, Fair =2 and Poor =1.

Table 7. Summary of user acceptance test

No	Criteria of evaluation	Poor	Fair	Good	Very Good	Excellent	Average
1	Simplicity to use and interact	0	0	0	1	4	4.8
2	Attractiveness of the system	0	1	1	1	2	3.8
3	Efficiency in time	0	0	0	1	4	4.8
4	The accuracy in deciding the types of disease	0	0	0	2	3	4.6
5	The ability of the system to make right conclusions	0	0	0	1	4	4.8
6	Importance of the KBS in the domain area	0	0	0	0	5	5
	Overall average						4.64

The evaluation result has witnessed that the system is simple to use for non-computer professionals through their pronouncements. More than 66% of them have rated it as excellent, and the remaining 34% have rated it as very good. From the expert judgment result, one can conclude that the system simplicity is because the graphical user interface of the system has been purposefully developed with Java Eclipse to be easy to use and navigate. The system's attractiveness is supported by 60% of the respondents who rated it as excellent or very good. This indicates that the system is attractive to users. The efficiency of the result was 80%, 20% excellent and very good respectively.

The accuracy of the system in deciding the type of disease achieves a better result from expert judgments, with 60% of the results being excellent and 40% of the results being very good. The result is outstanding for diagnosis and treatment. The importance of the system is rated as an important result by the respective domain area evaluators. Based on the results obtained, the overall average performance of the system for the diagnosis and treatment of chronic kidney disease with domain area assessment is 4.64 out of 5. When converted to percentage, the system acceptance recorded 92.8%, which shows that the system is really promising in medical diagnosis and treatment.

6. Discussion

Among the people of developing countries, chronic kidney disease is the main cause of death. This is because, in developing countries, there are no well-established prevention methods for chronic kidney disease, people have no awareness of the issue, and there is a shortage of specialists and health facilities [28]. In most developed countries, CKD is mostly related to old age, diabetes, hypertension, obesity, cardiovascular disease, and diabetic glomerulosclerosis, and hypertensive nephroscerosis, whereas, in developing countries, the common causes of CKD are glomerular and tubulointerstitial diseases which result from infections and exposure to drugs and toxins.

But, in developing countries, low-level quality of life like lack of clean water and lack of an appropriate diet are the main causes of chronic kidney disease. Hence, early detection is very crucial for both experts and patients to prevent and slow down the progression of chronic kidney disease to kidney failure [29].

Therefore, the researcher proposed a rule based medical intelligent system for chronic kidney disease diagnosis and treatment using the combination of the results from machine-learning and knowledge-based systems to help experts quickly diagnose the disease. To understand the domain area, the researcher conducted interviews with the domain expert, document analysis and observation. The proposed study also employs the KDD-Data Mining Process for data preparation, model building and deployment step. The researcher conducted three experiments using J48, PART, and JRip with Weka machine learning software. Finally, the JRip algorithm outperforms the other comparative algorithms with the highest classification accuracy.

The resulted knowledge of the best model built with machine learning algorithms is validated by domain experts and converted into a form suitable for SWI-Prolog and integrated with the JPL library. Hence, the prototype for the intelligent system, which provides diagnosis and treatment recommendations in Afan Oromo for all stages of CKD diagnosis and treatment, was fully developed using SWI-Prolog 7.7.13 and Eclipse IDE 8.0.

The proposed medical intelligent system has a knowledge base, an inference engine, an explanation facility, and a user interface. Then 40 test cases were prepared to evaluate the performance of the proposed system. Finally, a system performance test and a user acceptance test were conducted. A User acceptance test is performed based on seven evaluation criteria used in system rating. Selected domain experts are trained and use the system to evaluate how much the system meets their requirements.

Finally, the proposed medical intelligent system scored 92.8% in user acceptance evaluation and has registered 90% overall accuracy in system performance tests conducted with domain expert evaluators, which makes the system very fascinating in the medical sector even without any principal knowledge.

7. Conclusion

In this study, a medical intelligent system that supports the diagnosis of chronic kidney disease was developed by combining data mining techniques as a knowledge acquisition step with a knowledge-based system. The goal of combining data mining techniques with knowledge-based systems is to address the difficulty of knowledge acquisition and to acquire a high-quality and cost-effective knowledge base. Consequently, the proposed medical intelligence is supported by a simple GUI prototype, built from real datasets collected from the hospital, after which pre-processing steps and the use of a sufficient number of sample datasets have been able to cover the gap between the related work discussed in the literature review section of his study. The great merit of this study is it's simplicity for users at any level, without requiring special computer skills.

Hence, promising results were achieved in integrating machine learning induced patterns with a knowledge-based system for diagnosis and treatment of chronic kidney disease to advance the health system. The system work in a combined way that provides high capacity to diagnose disease and provides more effective knowledge representation and problem-solving capacity than limited human experts.

Further we are working to boost the benefits of integration of machine learning with the knowledge-based system and to develop fully integrated medical expert systems with the integration of case-based reasoning and rule-based reasoning systems based on the machine learning results on real-time datasets to achieve higher accuracy.

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