# Framework for Knowledge–Based Intelligent Clinical Decision support to Predict Comorbidity

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***Abstract*—Research in medicine has shown that comorbidity is prevalent among chronic diseases. In ophthalmology, it is used to refer to the overlap of two or more ophthalmic disorders. The comorbidity of cataract and glaucoma has continued to gain increasing prominence in ophthalmology within the past few decades and poses a major concern to practitioners. The situation is made worse by the dearth in number of ophthalmologists in Nigeria vis-à-vis Sub-Saharan Africa, making it most inevitable that patients will find themselves more at the mercies of General Practitioners (GPs) who are not experts in this domain of interest. To stem the tide, we designed a framework that adopts a knowledge-based Clinical Decision Support System (CDSS) approach to deal with predicting ophthalmic comorbidity as well as the generation of patient-specific care plans at the point of care. This research which is within the domain of medical/healthcare informatics was carried out through an in-depth understanding of the intricacies associated with knowledge representation/preprocessing of relevant domain knowledge. Furthermore, we present the Comorbidity Ontological Framework for Intelligent Prediction (COFIP) in which Artificial Neural Network and Decision Trees, both being mechanisms of Artificial Intelligence (AI) was embedded into the framework to give it an intelligent (predictive and adaptive) capability. This framework provides the platform for a CDSS that is diagnostic, predictive and preventive. This is because the framework was designed to predict with satisfactory accuracy, the tendency of a patient with either of cataract or glaucoma to degenerate into a state comorbidity. Furthermore, because this framework is generic in outlook, it can be adapted for other chronic diseases of interest within the medical informatics research community.**

***Keywords—Framework; Knowledge-based; Comorbidity; Clinical Decision Support System (CDSS)***

## I. Introduction

In today's contemporary times, a trend that seems to be gaining a lot of ground is the integration of intelligent mechanisms in the development of applications to enable them make decisions and attempt to behave like humans. This is widespread in Expert Systems, a branch of AI which Professor Edward Feigenbaum of Stanford University defines as the use of knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution [1]. Other areas gaining popularity include data mining, machine learning, neural networks, natural language processing, semantic web and so on. These different sub-fields of AI to a large extent make use of knowledge representation techniques. One of such techniques is ontology. "Ontology from the perspective of AI is a model that represents a set of concepts within a specific domain as well as the relationships between those concepts" for the purpose of communicating knowledge between entities and how they inter-relate [2]. In addition, ontology describes a formal specification of a certain domain. It is constituted by a specific vocabulary used to describe a certain phenomenon as well as a set of explicit assumptions as to the intended meaning of the vocabulary [3]. It is the implementation of concepts like ontology in the development of applications such as Decision Support Systems (DSSs) that make them act intelligently.

A DSS is a computer application designed to aid decision makers with the task of decision making. Hence, it can be said that CDSS associates health observations with health knowledge in order to influence the health choices made by clinicians to improve healthcare. A CDSS can be said to be an active knowledge system, where two or more items of patient data are used to generate case-specific recommendation(s) [4]. This means that a CDSS is a DSS that uses knowledge management to achieve clinical advice for patient care based on some number of items of patient data. This goes a long way in easing the job of healthcare practitioners, especially in areas where the number of patients is overwhelming. In medical domains like ophthalmology, there is a dire need of CDSSs, given the few specialists in this area of medical practice in regions of the world like Africa.

Co morbidity is defined as "any distinct clinical entity that has co-existed or may occur during the clinical course of a patient who has the primary disease under study" [5]. Within ophthalmology, co morbidity is commonly used to refer to the co-existence of two or more ophthalmic disorders. Comorbidity between cataract and glaucoma disorders have gained increasing prominence in ophthalmology within the past few decades. In a survey carried out in Sweden, it was substantiated that as much as 36% of patients with cataract also had ocular comorbidities [6].

More so, it has been observed that chronic diseases are often associated with comorbidities. In view of the foregoing National Centre of Health Statistics reported that some of the reasons that explain this trend range from inadequate hospital resources, long waits in hospitals and inadequate medical practitioners [7]. Therefore, one can conclude that comorbidity can be referred to as a condition caused by the debilitating effects of a prevailing ailment. Cataract (Catt) is one of such ailment that can trigger comorbidities especially glaucoma. It is worthy of note that in some instances, glaucoma can also be the prevailing ailment that triggers cataract. Hence, the comorbid condition of choice is that of cataract and Glaucoma (Gla) because both disorders are prevalent in sub-Saharan Africa.

Furthermore, in keeping with this established trend is the need for CDSSs of this nature to help GPs solve problems that are outside their knowledge-base/expertise (in this case, ophthalmology). Consequently, knowledge transition tools such as Evidence-Based Clinical Algorithms (EBCAs), which includes Clinical Practice Guidelines (CPGs) and Clinical Pathways (CPs), significantly go a long way in trying to reduce this care gap caused by the absence of an up-to-date knowledge [8]. CPGs are a function of a detailed and in-depth evaluation of scientific evidence about a specific medical condition/disease/procedure, designed for informed recommendations to aid clinicians in making decisions based on adequate evidence [9]. CPs on the other hand is used to implement the recommendations generated by the CPGs in actual clinical practice [10]. CPs also specifies the clinical processes as well as their workflow to implement the CPGs in a specific clinical setting. Consequently, a CPG entails *medical knowledge* whereas a CP entails *operational knowledge* about how to implement the CPG—i.e. the domain-specific protocols specifying the actual sequencing, decisions and scheduling of clinical tasks, as per the CPG, for the entire clinical course [11].

In view of the foregoing, a major challenge that arises is that which pertains to the alignment of multiple CPs of the comorbid diseases while conserving the integrity of medical knowledge and task pragmatics, and also ensuring patient safety. Hence, in this work, we modelled an intelligent/predictive CDSS for ophthalmic co-morbidity at the point of care. In addition, part of the emphasis was the examination and development of methods that use EBCAs to formalize, model, align and predict patient-specific clinical recommendations with a feedback mechanism, care coordination and decision support for ophthalmic comorbiditybased on substantial clinical evidence.

## II. Objectives and Methodologies

The main aim of this research was to design a predictive framework that adopts a knowledge-based CDSS approach to deal with ophthalmic comorbidity at the point of care. Therefore, preliminary methods for the formalization, modelling, alignment and prediction of EBCAs in comorbidities were determined and outlined. Focus was on the prevalent comorbidity of Cataract (Catt) and Glaucoma (Gla), because both are very rampant and common in sub-Saharan Africa and blacks in general. Accordingly, the objectives are to:

1) *Outline a stepwise description/exposition of how to build useful and valid knowledge-based CPs (guidelines/framework) through knowledge identification, acquisition, synthesis, formalization and alignment of relevant datasets especially those related to ophthalmic diseases of interest (cataract and glaucoma). This was achieved through an extensive review of literature leading to an in-depth understanding of the intricacies associated with knowledge representation/preprocessing of relevant domain knowledge. In doing this, the background natures of the ophthalmic diseases of interest are revealed.*

2) *identify relevant classification/predictive algorithms to provide intelligence for the proposed intelligent framework that makes the system adaptive and consequently improves on the existing framework. This was carried out by investigating the appropriate/suitable AI mechanisms aimed at giving adaptability to the proposed framework. This was done by looking at results obtained when such mechanisms were deployed in existing frameworks.*

3) *Design a framework that is diagnostic, predictive and preventive. Hence, the system when operational zed, will predict the chances of a patient with either of cataract or glaucoma to degenerate into a state comorbidity. This led to the adoption and embedding of Artificial Neural Network (ANN – feed-forward back multi-layer propagation) and Decision Trees (DTs – C5.0 algorithm) which are tools of AI into the framework to give it an intelligent (predictive and adaptive) capability.*

## III. Analysis of Existing and Related Frameworks, Their Features and Findings

This section introduces a discourse into the workings of existing and related frameworks especially COMET (Comorbidity Ontological Modeling &Execution) and PEDSS (Perinatal DSS).

### A. COMET Framework

The system in Fig 1 is an ontology-based decision support framework called COMET for handling comorbidities by the alignment of ontologically modelled CPGs. It is built to formalize, model, align and operationalize the evidence-based clinical algorithms of co-morbid Chronic Heart Failure (CHF) and A trial Fibrillation (AF) in order to provide evidence-based clinical recommendations, care coordination and decision support to GPs for effective management of CHF and AF.

Consequently, the framework addressed the following healthcare knowledge modelling issues:

1) *Modelling of healthcare knowledge, especially in terms of CPGs and CPs, to develop an ontology-based healthcare knowledge model for handling comorbid diseases.*

2) *Computerization of CPs to offer point-of-care decision support*

3) *Alignment of ontologically-modelled disease-specific CPs to handle comorbid diseases; and*

4) *The provision of computerized decision support for GPs, based on modelled CPGs and CPs, to assist them in handling chronic and comorbid diseases [12]*

Also an elaborate OWL-CP (Web Ontology Language – Clinical Pathway) ontology for comorbid CHF and AF was developed that can be executed to support the diagnosis and management of comorbid CHF and AF in a general practice setting. Hence, the COMET framework was implemented to handle three patient care scenarios:

*1) Patient that has CHF*
*2) Patient that has AF and*
*3) Patient with comorbidity of both AF and CHF*

COMET is accessible by web and is designed for GPs. It has been evaluated, both by simulated cases and by health professionals (GP and specialist), for its ability to handle single disease and comorbid care scenarios based on patient data and related constraints. The output at every phase was compared with the expected output as per single disease or comorbid management. Their results showed that the resultant sequence of plans and their outcomes are comparable to the CP knowledge [12].

### *B. Web-Based PEDSS Framework Using a Knowledge-Based Approach to Estimate Clinical Outcomes: Neonatal Mortality and Preterm Birth in Twins Pregnancies*

This system whose architecture is shown in Fig 2 and a description of its components in Table 1, adopts an improved classification method that was derived to improve the prediction of two distinct medical problems non-invasively:

*1) Neonatal mortality with information available at 10 minutes from birth and*
*2) Preterm birth in twin pregnancies before 22 weeks.*

The framework was developed by assessing various data mining methods with the aim of improving the classification of neonatal mortality and preterm birth in twin pregnancies. The major analyzed models were DTs and hybrid ANN to see which produced better outcomes. Positive findings related to the DT mechanism showed that same method can be applied to many other multi-factorial medical problems to improve its classification. This is given the fact that most published risk estimation models attempt to meet clinically acceptable sensitivity and specificity, in which case successful identification of positive cases have been met with much difficulty. Also, with unnecessary variables adding noise and complexity to the problem, it reduces the likelihood of identifying positive cases. A major aim of this framework was to incorporate the advantages of DTs to create a system able to predict the two perinatal problems already mentioned at an earlier stage while maintaining high sensitivity, specificity, Positive Predictive Value (PPV) and Negative Predictive Value (NPV)[13].

Thus, the new approach provides several improvements to better predict medical problems as outlined below:

*1) Pre-processed datasets run against C5.0 algorithm produced DTs superior to the DT-ANN hybrid method.*

*2) Two novel prediction models using DTs and hybrid ANN were evaluated. The DT prediction model had the highest performance outcome for predicting neonatal mortality (sensitivity = 62.24%, specificity = 99.95%, PPV = 72.34%, NPV = 99.92%) using information available within 10 minutes from birth, and preterm birth in twin pregnancies (sensitivity = 80.00%, specificity = 91.55%, PPV = 67.35%, NPV = 95.79%) before 22 weeks gestation. This was achieved using 5-by-2 cross validation. This indicates that the system is not over trained and provides good generalization. [NPV = Negative Predictive Value PPV = Positive Predictive Value].*

*3) Creation of a neonatal mortality prediction system for newborn to be assessed with data available from the first 10 minutes from birth non-invasively with excellent discrimination, exceeding the results of current standard predictions.*

*4) Creation of a preterm birth prediction system for a high risk population (for women pregnant with twins) non-invasively before 22 weeks gestation with excellent discrimination, exceeding the results of current standard predictions*

*5) The previous neonatal prediction method only focused on newborns after admission to NICU. This is the first attempt at predicting neonatal mortality in a heterogeneous population with data available at 10 minutes from birth.*

*6) Several improvements were made compared to past models: For the neonatal mortality case, the prediction of neonatal mortality non-invasively was reduced to data available at 10 minutes from birth using only 13 attributes, whereas the previous models required up to 12 hours from birth using 3 variables derived from invasive methods.*

*7) A conceptual framework for a secure web-based Perinatal Decision Support System (PEDSS) was consequently developed (with components as seen in Table 1) to provide audience targeted information and risk prediction of neonatal mortality and preterm birth in twin pregnancies [13].*

## IV. THE PROPOSED FRAMEWORK [COMORBIDITY ONTOLOGICAL FRAMEWORK FOR INTELLIGENT PREDICTION (COFIP)]

Having analyzed the PEDSS and COMET frameworks, a description of COFIP is given in this section. The framework diagram is as represented in Fig 3.

### *A. Knowledge Representation/Preprocessing*

This section is comprised of the knowledge identification, acquisition, synthesis, formalization and alignment layers. They are discussed below;

*a) Knowledge Identification/Acquisition Layer:* The cost and performance of an application depends directly on the quality of the knowledge acquired [14]. The purpose of this phase is to identify valid sources of relevant patient management knowledge as it pertains to two chronic disease conditions namely cataract and glaucoma. This is derivable from existing CPGs – a documentation that is predicated on evidence-based research and is thus a repository of knowledge aimed at providing guidance for decisions and criteria regarding diagnosis, management and treatment of specific disease conditions. The knowledge sources considered, not only entailed evidence-based recommendations but also specific tasks and procedures and their scheduling information. A number of knowledge sources are identified during this phase, including CPGs, institution specific drug management protocols, journal publications, and most importantly domain experts (in this case a consultant ophthalmologist and an optometrist at the Babcock University Teaching Hospital, Ilishan-Remo, Ogun State, Nigeria).

*b) Knowledge Synthesis Layer:* The knowledge synthesis phase involves the acquisition of the clinically useful task-specific heuristics from the identified knowledge sources (such as the CPGs) through the processes of selection, interpretation and augmentation of the guideline statements, tacit knowledge and logic. Where necessary, the heuristics will be further decomposed into atomic tasks and then organized in such a way as to develop two (cataract and glaucoma) CPs packages containing clear and relevant evidence-based diagnostic and therapeutic plans for patient care management, especially by GPs.Knowledge synthesis is a process in which one builds concepts in cooperation with others. It provides the opportunity for one's hypothesis or assumption to be tested. Social intercourse is one of the most powerful media for verifying one's own ideas. As such, participants in the dialogue can engage in the mutual co-development of ideas [15].

*c) Knowledge Formalization Layer:* Written sources such as textbooks and technical treatises are often not precise enough for transformation into descriptive logic: there may be competing accounts of the same phenomena, overlapping taxonomies and standards, or outright contradictions [16]. Hence in the knowledge formalization layer, the fused knowledge from the previous layer is modelled and formalized in terms of a dedicated CP ontology to be developed using the Web Ontology Language (OWL). Ontology is the standard knowledge representation mechanism for the Semantic Web framework. The choice of OWL is predicated on the fact that it offers declarative semantics that allows us to associate natural language descriptions with formal statements, thereby allowing human and machine readability of knowledge and subsequent execution of the knowledge. In this phase, the comorbid clinical processes in the CP ontology is hierarchically decomposed into component tasks that are based on the available evidence for specific single disease and comorbid scheduling constraints. This will ensure the conceptualization of the domain into an unambiguous model, thereby determining all implicit constraints on the relationships between the domain concepts, particularly to assist the alignment of concepts in handling comorbidities.

*d) Knowledge Alignment Layer*: The knowledge alignment layer involves ontology alignment—i.e. alignment of discrete and ontologically defined care plans in response to single disease or comorbid preconditions. The alignment of comorbid CPs is achieved at knowledge modelling level by developing a unified ontological model that encompasses the combined knowledge of aligned CPs. Also, knowledge alignment is tackled at the ontology level, implying that all ontological constraints about knowledge consistency will be observed in the ontologically-modelled Cataract-Glaucoma CP that entails a network of specific classes and the relationship between them. This is indeed a complex activity given the fact that the alignment of comorbid plans needed to take into account the medical correctness and clinical pragmatics of the resultant Cataract-Glaucoma CP.

### B. *Knowledge-Based Warehouse*

The knowledge-based warehouse is the repository for all the relevant domain knowledge gotten from the knowledge stratified into precondition sets A, B and C by the knowledge representation/preprocessing section of the framework. This knowledge-base is also updated through the workings of the results classification/prediction algorithms section where the rules and prediction modules are housed. It is structured such that knowledge is represented in such a way as to promote an efficient system that gives results that tend towards what is obtainable in reality. Therefore explicit/domain knowledge is synergized with tacit knowledge leading to an optimized outcome that helps to inform a patient-specific care plan/recommendation.

The optimized outcome from the prediction algorithms prior to generating the CPs is also used to update the knowledge-base. When this happens, a similar problem can be taken care of without subjecting it to the ANN and DT algorithms, an instance of learning having taken place. This implies a smooth transition from the knowledge-based warehouse to the CP formulation. However, where the patient already exhibits a full-blown comorbid condition it is not subjected to the results classification/prediction algorithms since the essence of that section is to predict the percentage tendency for the emergence of comorbidity where one of both diseases has developed. The section is composed of sub-modules, namely:

- Pre-Condition Set A – Cataract Disease: this houses the knowledge set akin to the cataract condition and sets up a need to predict whether the patient is likely to develop glaucoma vis-à-vis the comorbid condition.
- Pre-Condition Set B – Glaucoma Disease: this contains the knowledge set akin to the glaucoma condition and sets up a need to predict whether the patient is likely to develop cataract vis-à-vis the comorbid condition.
- Pre-Condition Set C – Cataract-Glaucoma Comorbid Condition: this houses the knowledge set akin to the cataract-glaucoma comorbid condition that sets up a need to initiate patient treatment plan and management.

### C. *Results Classification/Prediction Algorithm*

This section entails the mechanisms that make the framework adaptive. They include DTs and ANN which are both techniques of AI.

*a) Artificial Neural Network:* ANNs are powerful non-linear mapping structures and are especially useful for modelling relationships which are unknown. ANNs function similar to the human brain and can solve problems involving data that is complex, non-linear, imprecise and/or noisy [17]. The human brain is a collection of more than 10 billion interconnected neurons that is able to receive process and transmit data. The human brain also consists of a highly parallel computing structure to support computationally demanding perceptual acts and control activities [18]. ANNs were developed as generalized mathematical models to represent the biological nervous system [18]. The ANN is trained to detect a pattern between the inputted data and the related output value from a dataset. After training the set, the ANN can be used to predict the result of a newly inputted data [17].There is various types of ANNs including feed-forward, recurrent neural network and probabilistic network. The ANN structure used in this thesis is referred to as feedback oriented propagation multi-layer perception.

*b) Decision Trees:* Decision trees are favoured in the data mining community due to its highly interpretable structure, allowing business end users and analysts to understand the models, whereas neural networks are difficult to understand and interpret [19]. A decision tree consists of a root node, branch nodes and leaf nodes. The tree starts with a root node, is further split into branch nodes (each of the nodes represent a choice of various alternatives), and terminates with a leaf node which are un-split nodes (represents a decision) [20]. Classification of decision trees are conducted in two phases, including the tree building (top down) and tree pruning (bottom-up). Tree building is computationally intensive, and requires the tree to be recursively partitioned until all data items belong to the same class. Tree pruning is conducted to improve the prediction and classification of the algorithm and to minimize the effects of over-fitting, which may lead to misclassification errors [21]. There are a number of decision tree algorithms that exist including Classification and Regression Trees (CART), Iterative Dichotomiser 3 (ID3), C4.5 and C5.0. This thesis work uses C5.0 based decision tree algorithm which is an improvement over C4.5, which itself is an improvements over the earlier ID3 method.

*c) Result Comparison and Optimization:* The result comparison and optimization module is responsible for synergizing the outputs generated by the different classification/prediction algorithms i.e. the ANN and DT mechanisms so as to settle for an optimized output. The entire workings of the different modules in this unit are all geared towards finding a healthy association between the domain knowledge and tacit knowledge in other to make the overall system operation with some measure of expertise akin to a human expert. Tacit knowledge has to do with unwritten, unspoken, and hidden vast storehouse of knowledge held by an individual, based on the persons' emotions, experiences, insights, intuition, observations and internalized information. Tacit knowledge is integral to the entirety of a person's consciousness, is acquired largely through association with other people, and requires joint or shared activities to be imparted from one person to another. Like the submerged part of an iceberg it constitutes the bulk of what one knows, and forms the underlying framework that makes explicit knowledge possible. When the inputs from the knowledge-base is subjected to analysis by the ANN and DT mechanisms their outputs are compared and the outcome are optimized for the generation of rules with which predictions get carried out.

### D. Intelligent Clinical Pathway Generator System

The intelligent clinical generator system unit is composed of rules that are a function of the results comparison/optimization module which is used to make predictions that gets to inform the generation of patient-specific care plans. It also contains a feedback mechanism.

*a) Rules and Prediction:* The rules module receives an optimized output upon which rules are generated and subjected to further coordinated analysis that becomes the yardstick for the prediction of the tendency for comorbidity. Once this is established the predicted values become the benchmark upon which generation of patient-specific care plans and recommendations take place.

*b) Patient-Specific Care Plans/Recommendations:* This system adopts patient-specific CPs/recommendations as against case-based CPs/recommendations because the modern patient wants to be treated as an individual person and not just as a statistic [22]. Patients want to know their own risk, not just a parameter regarding a class of people similar to them. This feature is highly enhanced through the deployment of ANNs which are able to reproduce the dynamical interaction of multiple factors simultaneously, allowing the study of complexity which is very important for a researcher interested in in-depth knowledge of a specific disease or to better understand the possible implications relative to strange associations among variables. This has to do with what is called "intelligent data mining". But on the other hand ANNs can also help medical doctors in making decisions under extreme uncertainty and to draw conclusions on individual basis and not as average trends.

*c) Feedback Mechanism:* In view of the fact that this framework serves as a platform for implementation and translation into a real system, a feedback mechanism is sacrosanct and must be included. More so, a typical developer may find it difficult to adapt a framework that is without a feedback system during implementation [23]. Hence, the proposed framework holds an extension to one. The schematic diagram in Fig 4 shows a typical feedback mechanism which is a sub-set of the patient-specific care plan generator system. The feedback mechanism is composed of functionalities that:

1) *Describe diagnosis:*
- Inform patient about disease (you're diagnosed as suffering from…)
- present supporting evidence for disease

2) *Alleviate patient fears:*
- describe improvements

3) *Describe future prospects.*
4) *Describe disease triggers:*
- present background information
- List triggers mentioned by the patient.
- List triggers mentioned by doctor.
- Suggests methods of avoidance.

5) *Describe drug prescription.*
6) *Describe need for long term effort.*

*d) Discussion of the Underlying Processes:*

*1) The patient information is fed into the system (See Fig 5). The patient information includes age, race, gender etc. medical history such as surgery, ocular disease, eye surgery, trauma etc. Questions about the patient's sight are also included. The patient's information is then subjected to the knowledge representation and preprocessing.*

*2) Knowledge representation/preprocessing has four layers: identification/acquisition, synthesis, formalization and alignment layers.*

- Knowledge identification/acquisition layer identifies valid sources of relevant patient management knowledge as it pertains to two chronic disease conditions namely cataract and glaucoma. The knowledge is derived from existing CPGs.
- Knowledge synthesis layer involves the acquisition of the clinically useful task-specific heuristics from CPGs through the processes of selection, interpretation and augmentation of the guideline statements, tacit knowledge and logic.
- In the knowledge formalization layer (semantic layer) the synthesized knowledge will be modelled and formalized in terms of a dedicated CP ontology to be developed using the Web Ontology Language (OWL).
- Knowledge Alignment layer involves ontology alignment of discrete and ontologically defined care plans in response to single disease or comorbid preconditions.

*3) The preprocessed results from the knowledge representation unit are passed into knowledge base warehouse for dynamic storage and updating. The knowledge-based warehouse is updated through the rules and prediction unit. Here, the preconditions are segmented and classified into one of cataract, glaucoma or comorbid precondition sets. If it is the comorbid condition the patient-specific care plan is generated straight away. Else, the disease identified (cataract or glaucoma) is subjected to the classification/prediction algorithm. The two algorithm used are ANN and DT. The two are used to complement each other's strengths and weaknesses as the case may be. The result from ANN and DT are compared for optimization and the best values are chosen and used to generate the rules.*

*4) The rules generated are made from the result of the optimization and they are used to update the precondition sets A and B (cataract and glaucoma) contents in the knowledge base warehouse. Once the condition is ascertained, the patient-specific care plan is generated.*

## V. Conclusions and Implications

This research paper entails the design of an adaptive framework (COFIP) that is diagnostic, preventive and predictive. This is because COFIP was designed to predict with satisfactory accuracy, the tendency of a patient with either cataract or glaucoma to degenerate into a state of comorbidity.

Furthermore, because this framework is generic in outlook, it can be adapted for other chronic diseases of interest within the medical informatics research community.

### *A. Recommendations and Future Work*

Having built the predictive framework, full implementation will be carried out as follows:

*1) Build useful and valid knowledge-based CPs (guidelines/framework) through the acquisition of relevant data sets especially those related to ophthalmological diseases (Catt-Gla).*

*2) Model the selected ophthalmological diseases such that the diagnostic and treatment concepts show inter-relationships in formal language in ways that curb every form of possible ambiguity. This is carried out in such a way as to ensure that the encoded knowledge and the underlying decision logic can be executed through computerized clinical decision support systems to provide patient-specific CPG-based recommendations.*

*3) Systematically align the designed model to handle ophthalmologic diseases without compromising the integrity of medical knowledge, care coordination and safety of patients.*

*4) Fully operationalize the designed framework that is diagnostic, predictive and preventive. Thus, the system when implemented will predict the chances of a patient with either of Catt or Gla to degenerate into a state comorbidity.*

### *B. Summary*

The coexistence of cataract and glaucoma accounts for alarming levels of visual impairment in our society vis-à-vis impairment of quality of life and hence increases the burden of illness, care plan, patient management and related concerns. A viable method to reduce the menace of blindness and other related conditions is to engage GPs in the management of cataract and glaucoma as well as its co-morbidities, because GPs are the first point of care for most patients. There are challenges in the diagnosis of glaucoma for instance given that many of its clinical features are time-specific and sometimes not obvious though present.

To make matters worse, concurrent presence of cataract complicates the management of either condition as the choice of treatment depends on individual factors of each disease as it manifests in the patient. EBCAs such as CPGs and CPs have the propensity to narrow this gap [8]. They can by assisting GPs to undertake complex diagnostic and management scenarios resulting from the comorbidity of cataract and glaucoma. In view of the foregoing we have designed an improved framework that enhances the classification/prediction of comorbidities that bring with it adaptability that helps to guide patients with one chronic disease to manage their condition so as to prevent the degeneration of their condition to full-blown comorbidities. COFIP was designed to improve on the existing COMET framework that is not adaptive.

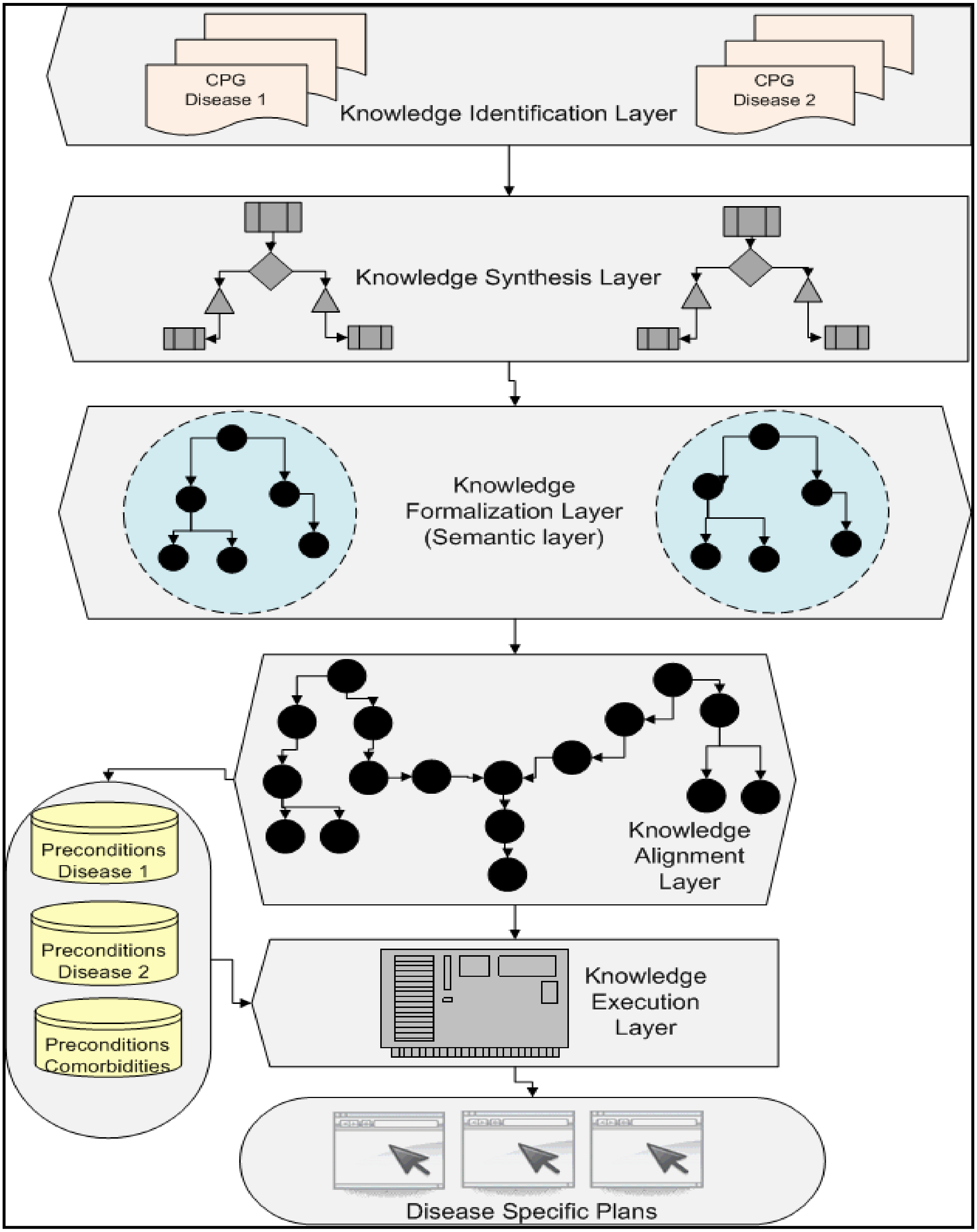


Fig. 1. COMET Framework [12]

TABLE I. COMPONENTS FOR A WEB-BASED PEDSS [13]

| | **Components** | **Description** |
|---|---|---|
| 1 | Authentication Server | Authenticates users into the system |
| 2 | Content Management System (CMS) | The heart of the system used to display, search, and process the data, based upon the user request |
| 3 | Workflow Engine | Required to automate alerts, warning and actions |
| 4 | External Data Source | A repository of the patient, or user information |
| 5 | Directories | A database of user information, etc. |
| 6 | Other Web Servers | Other servers required to operate the PEDSS |
| 7 | ASP.Net, XML, HTML | The interface presented to the user |

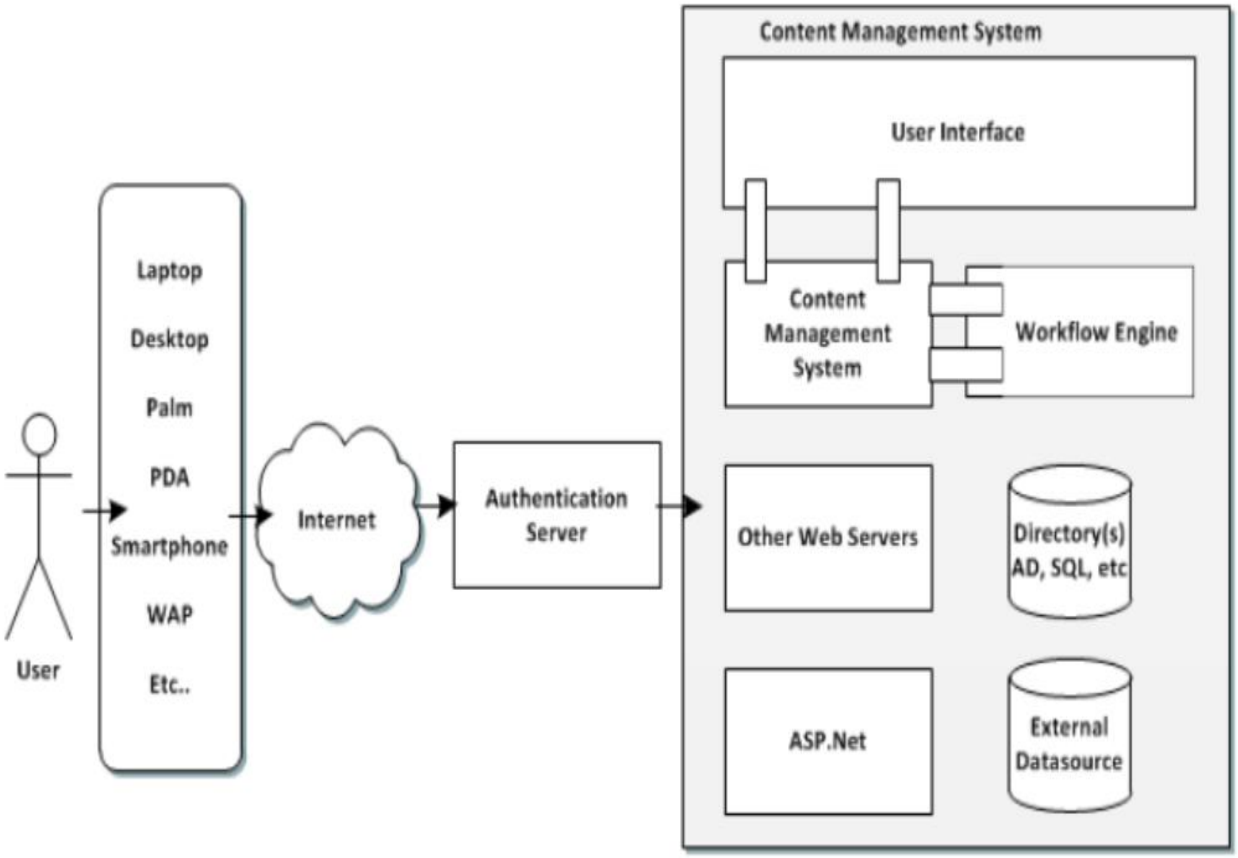


Fig. 2. System Architecture of Web-based PEDSS [13]

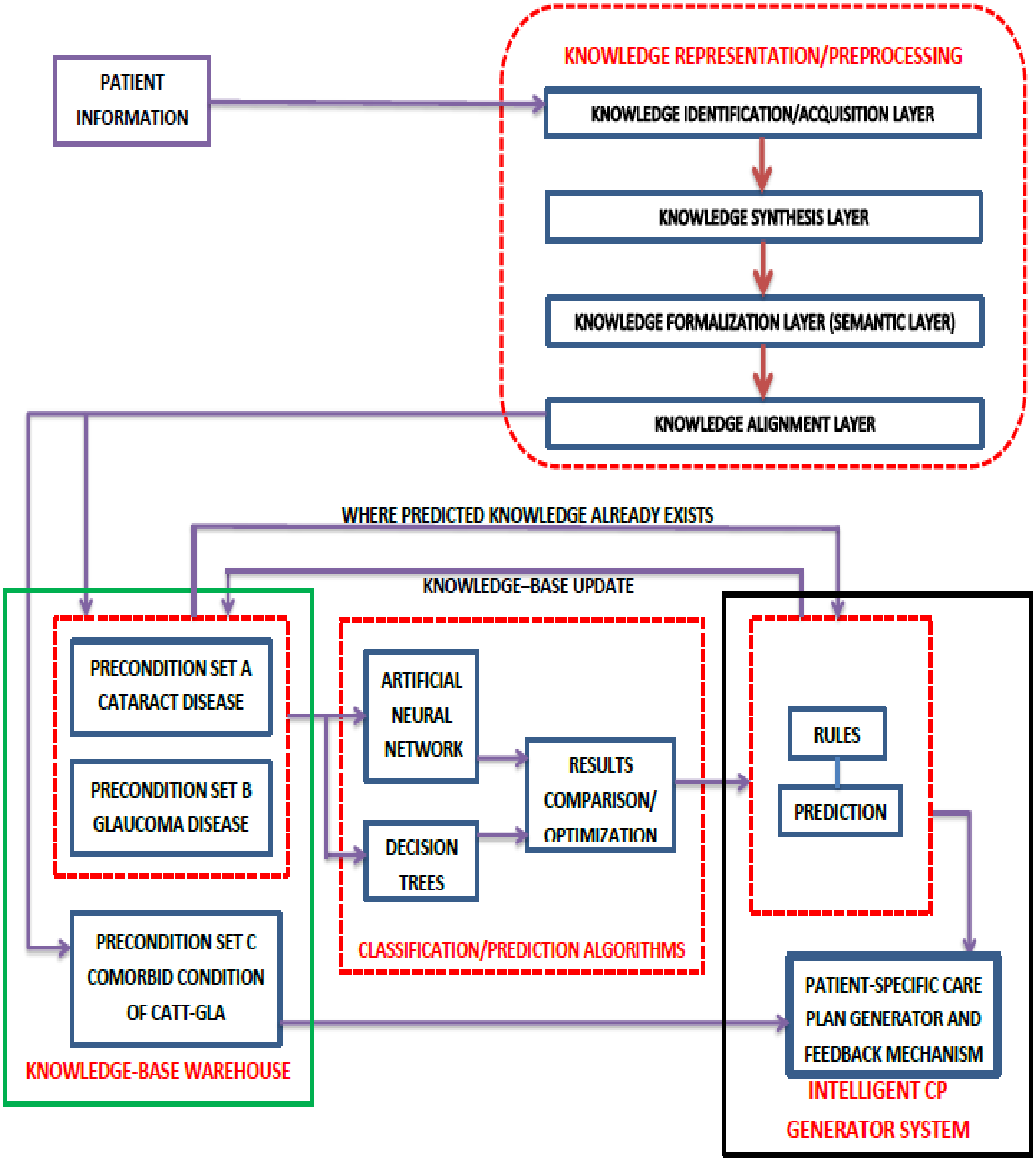


Fig. 3. The Proposed (COFIP) Framework

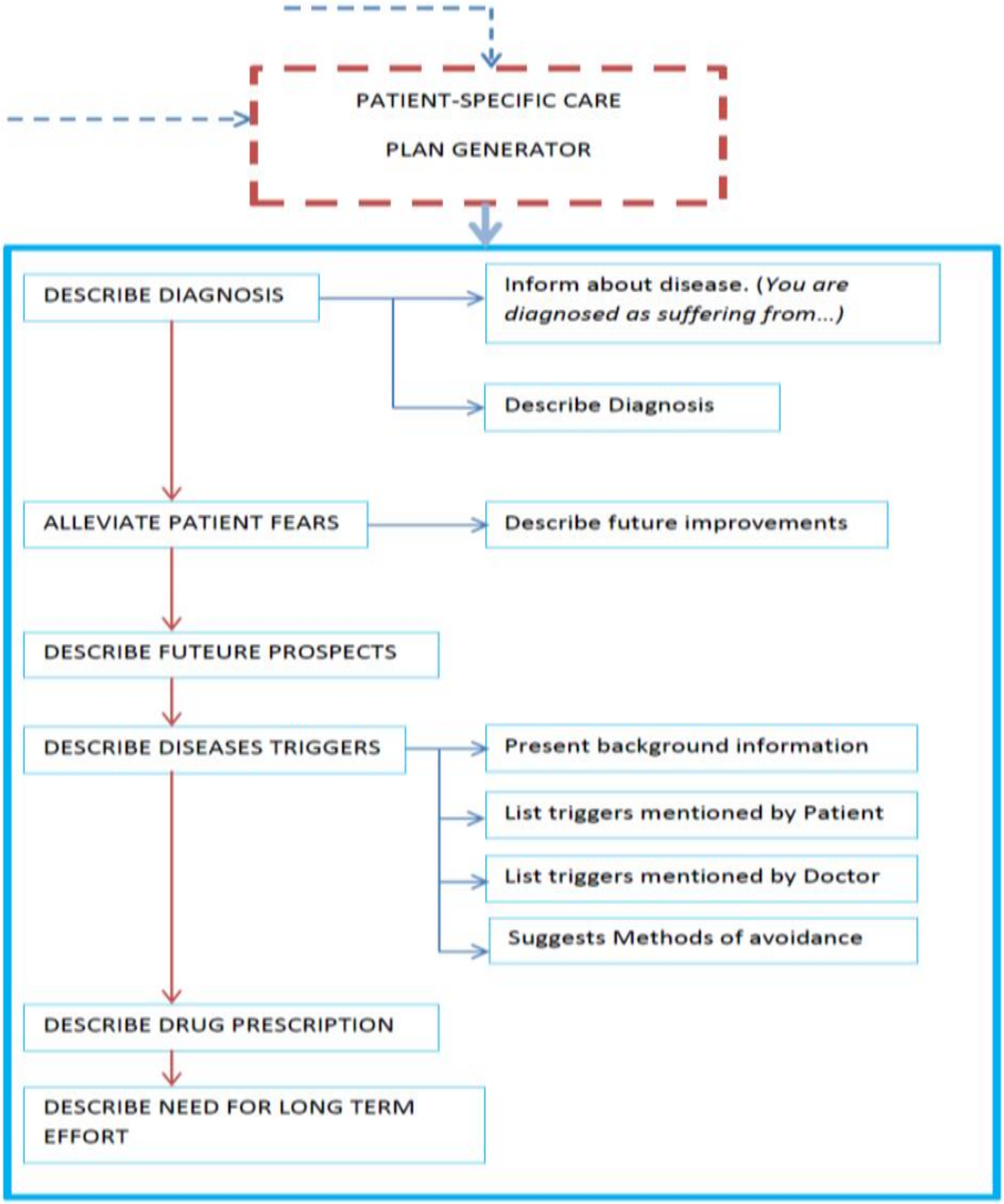


Fig. 4. Feedback Mechanism

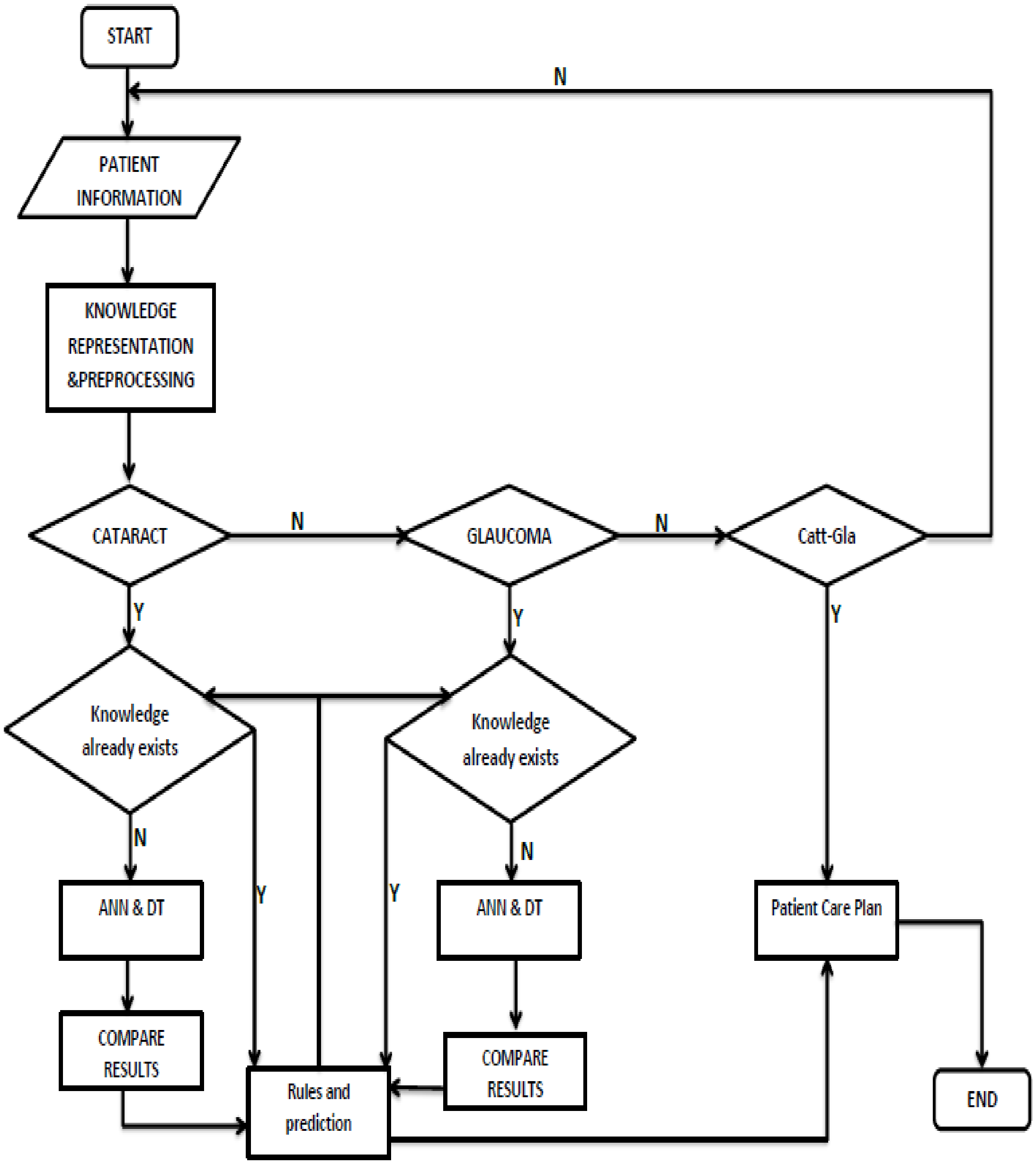


Fig. 5. Flowchart of COFIP


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