

A Medical Intelligent Process Model Using Ontology Based Technique

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Abstract - The complexity of patient care, the rapid expansion of medical knowledge, and the requirement for more precise decision-making has made the demand for creative solutions inevitable, a Medical Intelligent Process Model (MIPM) utilizing an ontology-based appears as a promising way to overcome this obstacle and unleash the full potential of healthcare systems. The development of MIPM is motivated by lack of quick access to relevant medical information, advanced tools for treatment planning and clinical decision-making. This work is aimed at developing a structured and knowledge-driven framework that leverages ontology, a formal representation of domain knowledge, to enhance various aspects of healthcare. Object-Oriented Analysis and Design Methodology (OOADM) was adopted in the design of the system as we desired to build a usable and evolvable application. For effective implementation of this work, medical dataset from Kaggle was utilized; ontology-based technique was used with confusion matrix to test the system. MySQL database engine was used to model the data used, with Laravel-migration to integrate Ontology in the database. Python, Hypertext Markup Language (HTML), Hypertext Preprocessor (PHP), Cascaded Style Sheet (CSS) and Java Script were used in the actual development of the system. A medical intelligent process using ontology-based technique was developed.

Keywords - *Ontology-based, Model, Database, OOADM and Healthcare, Laravel Migrations.*

I. INTRODUCTION

Electronic health records, clinical notes, medical imaging, and other data are only a few of the many types and sophisticated types of data generated by the healthcare industry. The objectives of better patient care, fewer errors, and faster medical research are what motivate the need for effective data management and utilization in the healthcare industry. Healthcare data difficulties may be addressed with ontologies, which give an organized method of representing knowledge in a machine-readable fashion. Ontologies present a viable option to handle data difficulties in healthcare because they offer an organized method of representing knowledge in a machine-readable fashion. Ontologies provide a sound basis for sharing domain knowledge between human and computer programs, or between computer programs. An ontology normally defines concepts (or classes), individuals (or instances), properties, relationships and their constraints. Ontology is as a formal, explicit specification of a shared conceptualization and conceptualization is an abstract model of some phenomenon in the world by having identified the relevant concepts of that phenomenon [2]. Explicit means that the type of concepts used, and the constraints on their use explicitly defined. Ontologies allow more complete and precise domain models. Ontologies are intended to be shared and reused, and the approach perceived to be beneficial. Ontology-based design has advantage of being syntactically correct and semantically consistent as a model. Sometimes, the health records of the patients and detail of the doctors are stored in different hospitals or stored in different location of the database, it is difficult to collect these

records [3]. Ontologies are one of the most successful ways of representing actionable knowledge in biomedicine. For that, an ontology can be constructed to resolve these problems and to make correct decision at an emergency period [4]. Ontology-based search system gives a user more meaningful query results than the normal search system, which queries data with syntactic parameters. The query result is based on data retrieval methods [5]. Ontologies provide a common language to express the shared semantics and consensus knowledge developed in a domain. Ontology technique will provide quick access to documents and information with the help of taxonomy created from the concepts, called a concept map, with the incorporation of ontology array indexing [6]. This research will explore this to develop an intelligent medical process.

The increasing demand to streamline medical processes, better decision-making, and improve overall patient care is the motivation behind this research. Traditional healthcare systems are often faced with the vast amount of heterogeneous and unstructured data, hindering the seamless flow of information critical for timely and accurate decision support. By incorporating ontology-based techniques, these gaps are bridged and pave the way for a more intelligent and adaptive medical framework. The primary objectives of this work are to introduce the concept of a medical intelligent process model (MIPM) as a means to optimize medical workflows (Figure 1); explore the role of ontology-based techniques in structuring medical knowledge and facilitating intelligent decision support; and highlight the potential impact of MIPM on enhancing healthcare outcomes and resource utilization. The focus of this work is on the creation and application of a special

ontology-driven strategy in the medical area. The proposed MIPM is designed and evaluated, with an emphasis on its practical applicability and benefits in real-world healthcare settings.

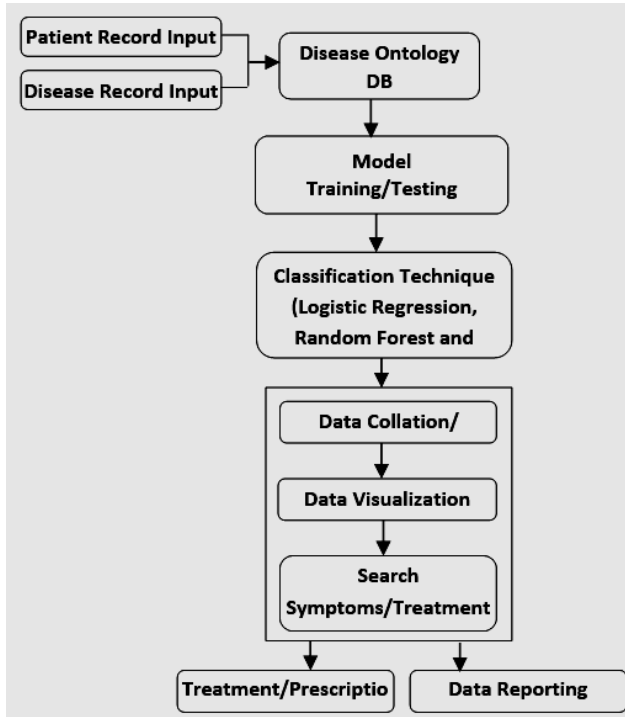


Figure 1. Workflow of MIPM using ontology based technique

This paper is structured as follows - Section I introduces the work stating the background, purpose of the work, and objectives, as well as its scope. While section II focuses on related works on medical intelligence process models using ontology-based techniques, with the summary of the reviewed literature. Section III provided an analysis of the materials and methods, including information on the experimental setup, dataset and feature set descriptions, and methodology details. The system's implementation, evaluation, and discussion of the outcomes were covered in Section IV. The work's conclusion, recommendations, and areas for future work are outlined in Section V.

II. REVIEW OF RELATED WORKS

Recent advances in e-healthcare has led to a surge in opportunities for the design and implementation of Patient-Centered Healthcare (PCC) delivery models across small to large scale medical practices. Proactive distribution of relevant and reliable information across robust communication technologies that facilitate a network of support around patients is fundamental to these advances. In this section, a review of existing systems in medical field for promoting medical record keeping and medical intelligent systems is presented.

An evolutionary approach to software testing Ontology development was introduced [2]. The authors stated that software testing is a growing discipline that sees the need for a standardized ontology. In the same vein, they opined that software testing ontology (STO) is a formal and an explicit description of concepts and relationships used to describe various aspects of software testing artifacts. This work describes the steps used to build the base for the standard STO that, in turn, can be extended and further enhanced towards standardization. Nor, Mansoor and Shadia [2] further stated that the evolving STO is envisioned to be an important addition towards enriching the functionality of semantic software testing tools and systems. According to the authors, the base STO covers the terminology found in standard testing glossary which can be expanded to cover the whole hundreds of concepts related to software testing based on the previously mentioned standard testing glossary. This is large enough to supply accurate reasoning terms for semantic systems such as Semantic Test Case Management System or any other that concerns software testing.

An ontology-based personalization of health-care knowledge to support clinical decisions for chronically ill patients was proposed by [7]. The authors stated that chronically ill patients are complex health care cases that require the coordinated interaction of multiple professionals [7]. A correct intervention of these sorts of patients entails the accurate analysis of the conditions of each concrete patient and the adaptation of evidence-based standard intervention plans to these conditions. There are some other clinical circumstances such as wrong diagnoses, missing information, unobserved related diseases or prevention, whose detection depends on the capacities of deduction of the professionals involved.

David and Francis [7] introduced ontology for the care of chronically ill patients and implement two personalization processes and a decision support tool. The first personalization process adapts the contents of the ontology to the particularities observed in the health-care record of a given concrete patient, automatically providing a personalized ontology containing only the clinical information that is relevant for health-care professionals to manage that patient. The second personalization process uses the personalized ontology of a patient to automatically transform intervention plans describing health-care general treatments into individual intervention plans. Finally, the ontology is also used as the knowledge base of a decision support tool that helps health-care professionals to detect anomalous circumstances such as wrong diagnoses, missing information, unobserved related diseases, or preventive actions.

Marut [9] developed an Ontology-based clinical reminder system to support chronic disease healthcare and suggested that improving quality of healthcare for people with chronic conditions requires informed and knowledgeable healthcare providers and patients. Decision

support and clinical information system are two of the main components to support improving chronic care. Marut [9] in his paper described an ontology-based information and knowledge management framework that is important for chronic disease care management. Ontology-based knowledge acquisition and modeling based on knowledge engineering approach provides an effective mechanism in capturing expert opinion in form of clinical practice guidelines. The framework focuses on building of healthcare ontology and clinical reminder system that link clinical guideline knowledge with patient registries to support evidenced-based healthcare. He describes implementation and approaches in integrating clinical reminder services to existing healthcare provider environment by focusing on augmenting decision making and improving quality of patient care services. The paper was focused on clinical reminder service and didn't integrate electronic health record (EHR) standards and this is the research gap established in his work.

Agustina, Alejandra and Nieves [10] reviewed and made a comparison of Ontology-Based Data Integration Methods. The researchers stated that data integration system provides a uniform interface to distributed and heterogeneous sources. These sources can be databases as well as unstructured information such as files, HTML pages, etc. One of the most important problems within data integration is the semantic heterogeneity, which analyzes the meaning of terms included in the different information sources [10]. This survey describes seven systems and three proposals for ontology-based data integration. An important feature is that all of them use, in some way, ontologies as the way to solve problems about semantic heterogeneity. In the paper, they show similarities and differences among the systems by providing a framework for comparison and classification.

Asogwa et al. [6] in their work titled study on theoretical aspects of ontology-based and virtual data integration in medical intelligence process and its applications presented the key concept of the developed business intelligence model. They adopted ontology-based (OBDI) and virtual data integration (VDI) techniques with the ability to ensure abstraction of data that comes from multiple sources in varying schemas, syntactic accuracy and also has a seamless transition from data into information, then into action. Their model leveraged the benefits of ontology-based and virtual data integration techniques in a business intelligence environment. The result was an intelligent, agile, adaptive, user-friendly, real-time solutions as well as structural (schema), syntactic (format) and semantic (meaning) heterogeneity correct data model to decision-making for business users [6].

Bostjan and Vili [8] proposed an automating ontology based information integration using service orientation. They

argued that with the rise of the Internet, globalization and the increasing number of applications used inside organizations, there is an emerging need to integrate information across heterogeneous information systems. Service oriented architecture (SOA) is seen as a general answer to intra-organisational as well as inter-organisational integration problems [8]. While service oriented systems have been well studied, there are still some challenges remaining unanswered. One of them is automation of service execution. The paper proposes a method for automated execution of Web Services. Based on Web Service execution automation, the proposed approach is bridging the gap between ontology based integration and service oriented architecture by enabling dynamic and transparent integration of information which is provided by services. A key limitation of this work is the splitting of the query into static and dynamic queries which was not addressed fully as identified in the work.

III. MATERIALS AND METHOD

This section focuses on integrating patient data, medical domain knowledge, patient diseases, symptoms, and recommended treatment recommendations, including patient follow-up assessments, using an ontology-based framework. We constructed the disease registry database using an ontology-based methodology. To put this framework into practice, a medical intelligence process model was created, which allows standard assessment protocols to be automatically chosen and tailored to the unique circumstances of each patient. We used machine learning technique to access our results on a three hundred and forty nine (349) data set obtained from Kaggle. 80% of the dataset was used for training of our model while 20% was used for the testing. The system was built with the available data set obtained from kaggle.com with other related literature review such as journal or articles.

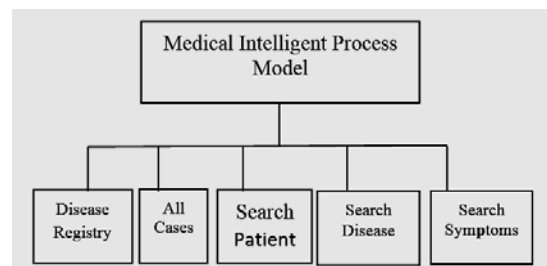


Figure 2. HIPO diagram of MIPM Model

The performance of our model was summarized and evaluated using Confusion Matrix with Python programming language. A hierarchical process input output (HIPO) diagram of the Medical Intelligent Process Model (MIPM) was developed using Ontology-based technique (Figure 2). The MIPM system has five (5) modules as shown in Figure 2.

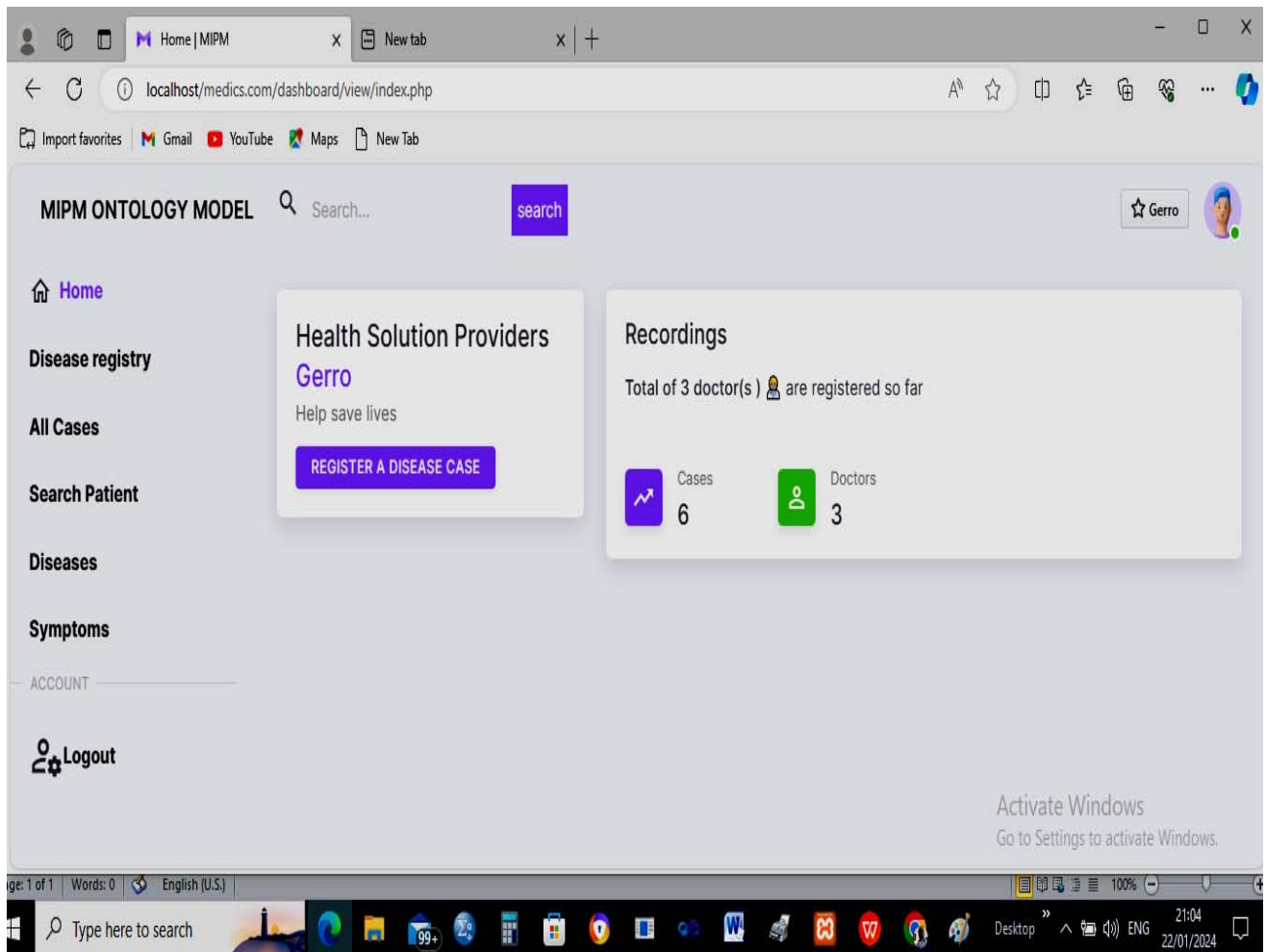


Figure 3. Home Page of MIPM Ontology

A. Disease/ Registry:

The disease registry as shown in figure 4 below is used to create new diseases into the ontology-based disease registry database.

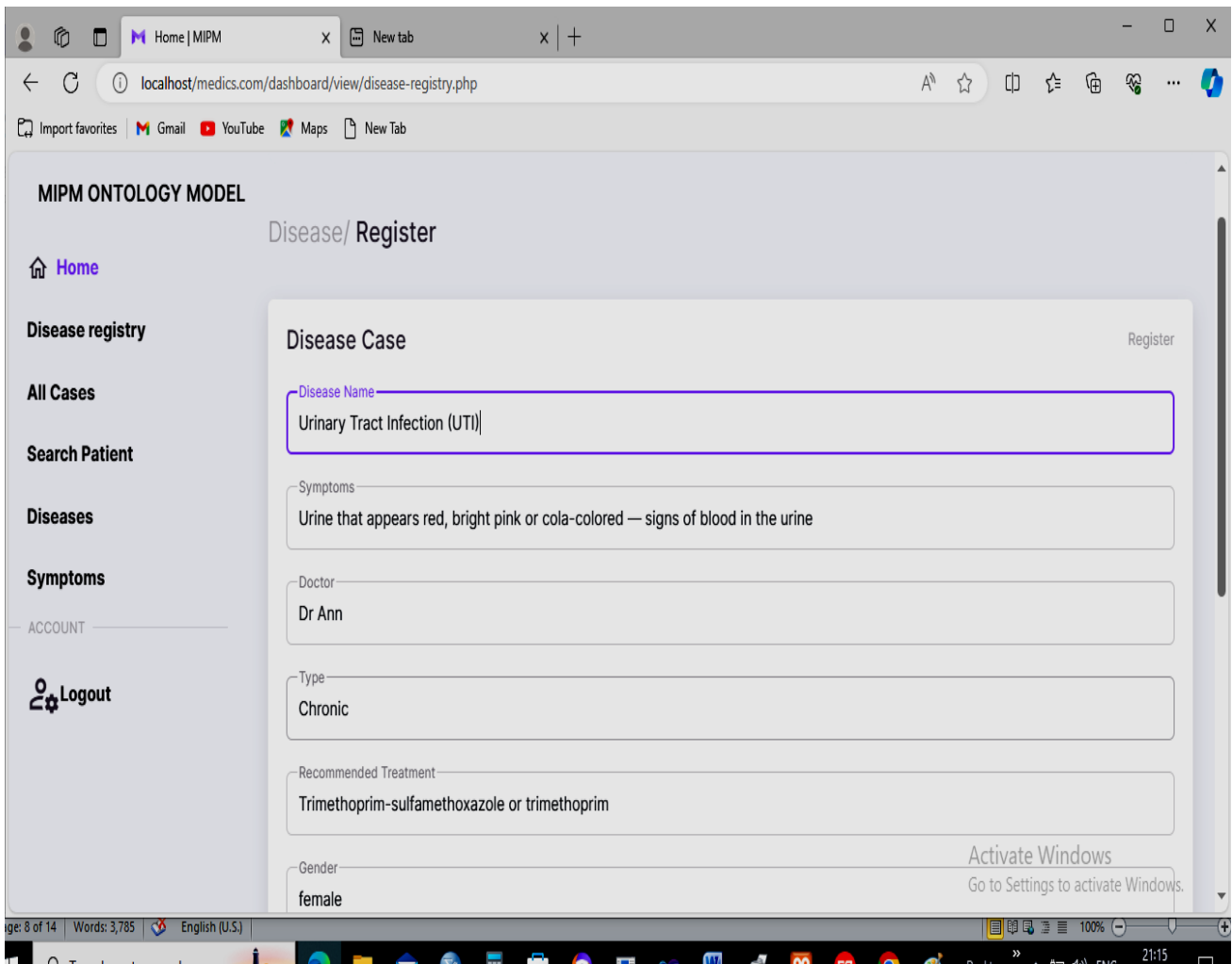


Figure 4. Disease / Registry of MIPM Ontology

It contains the disease name, symptoms, doctor name, recommended treatment, gender, blood group, treatment status, rating with the help of Laravel-migration ontology, it is easy to find the type of disease, the recommended treatment, the status of the patient and the effectiveness of the treatment and hospital name.

B. Search/ Symptoms:

The search symptom is used to search for the patient symptoms. Once a query is sent, with the help of Laravel-migration ontology, it is easy to find the type of disease, the recommended treatment, the status of the patient and the effectiveness of the treatment.

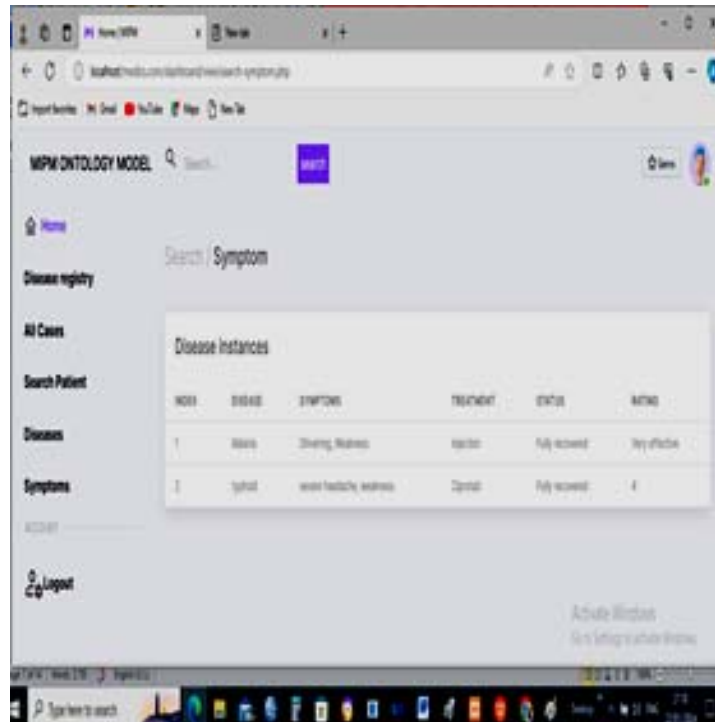


Figure 5. Search/Symptoms of MIPM Ontology

C. Ontology-based Approach

C1. Database Creation Integrating Ontology

In order to integrate Ontology in the database, we explored Laravel migration which is a crucial aspect of database and a popular PHP web application framework. This allows us to control and manage the database schema making it easy to evolve the database structure over time and collaborate with other applications. Ontologies often rely on formal languages like OWL (Web Ontology Language) to describe concepts, relationships, and constraints. Migration serves as a practical implementation of these formal structures.

The `.env` file is used to store configuration parameters for different environments, such as local development, staging, and production.

```

11  DB_CONNECTION=mysql
12  DB_HOST=127.0.0.1
13  DB_PORT=3306
14  DB_DATABASE=laravel
15  DB_USERNAME=root
16  DB_PASSWORD=

```

Figure 6. A section of the `.env` file

When running Artisan commands that involve database setup, Laravel uses the values from the `.env` file to determine the database connection details. This was defined with the command: `php artisan migrate`. Laravel uses the `config` function to access configuration values throughout the application. Behind the scenes, this function reads the configuration values from the configuration files, including those specified in the `.env` file.

C2. Creating Migrations

To create a new migration, we used the `make:migration` Artisan command. This command generates a new migration file in the `database/migrations` directory. For example the command:

```
php artisan make:migration create_example_table
```

will create a migration file named something like `2023_01_01_000000_create_example_table.php`, where the timestamp is appended to ensure proper ordering of migrations the tables created as showed in figures below.

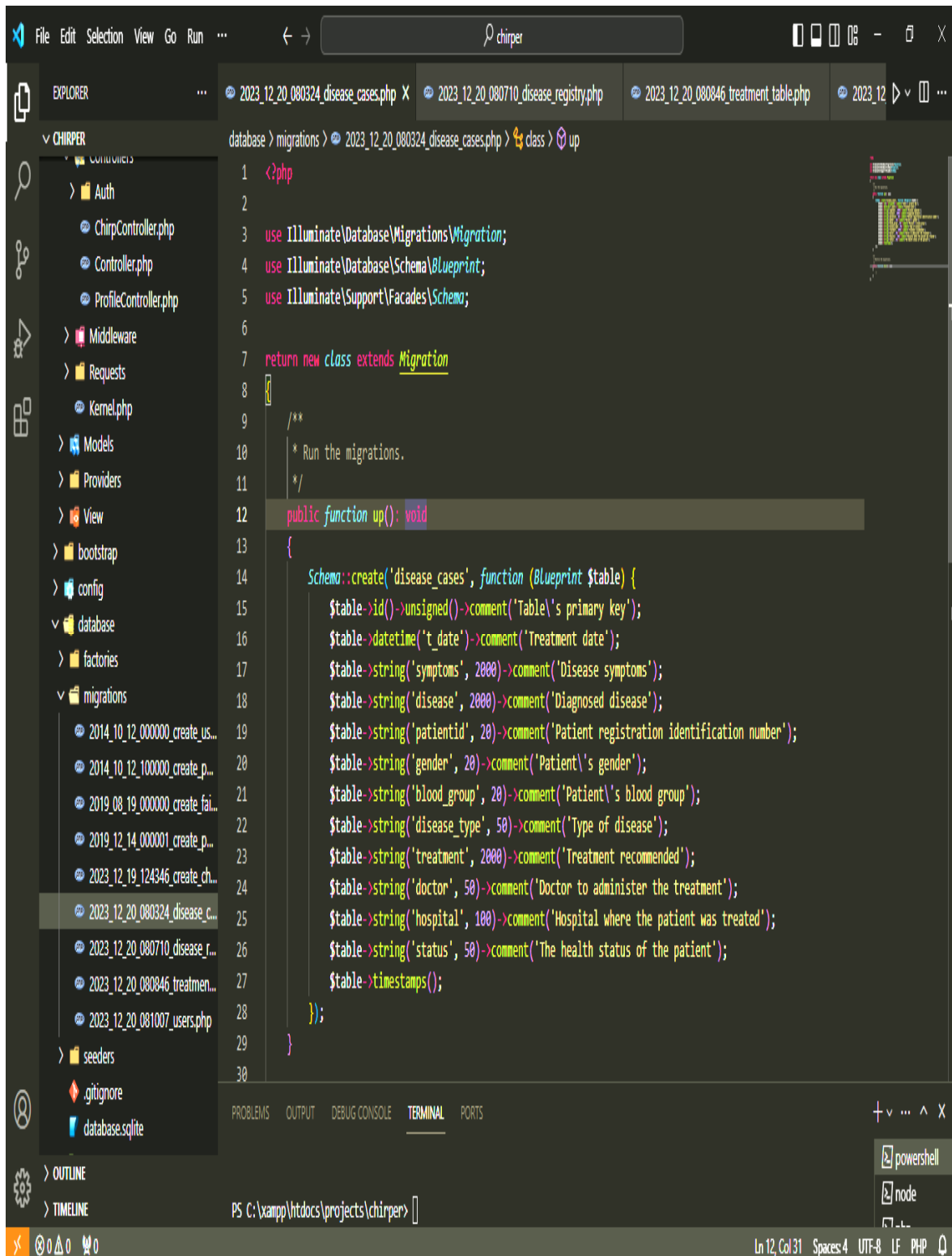


Figure 7. Migration file for creating the disease cases table

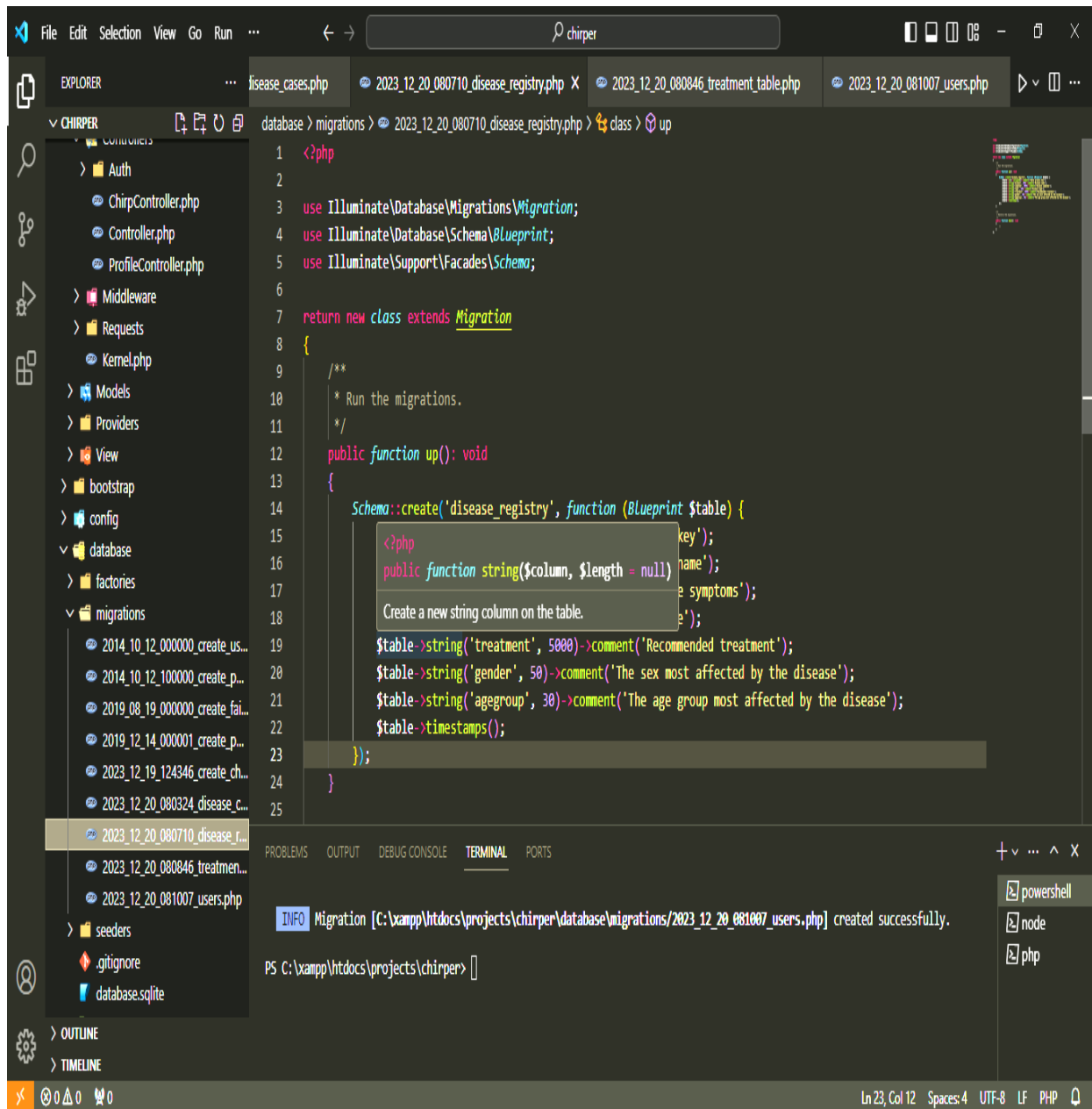


Figure 8. Migration file for creating the disease cases table

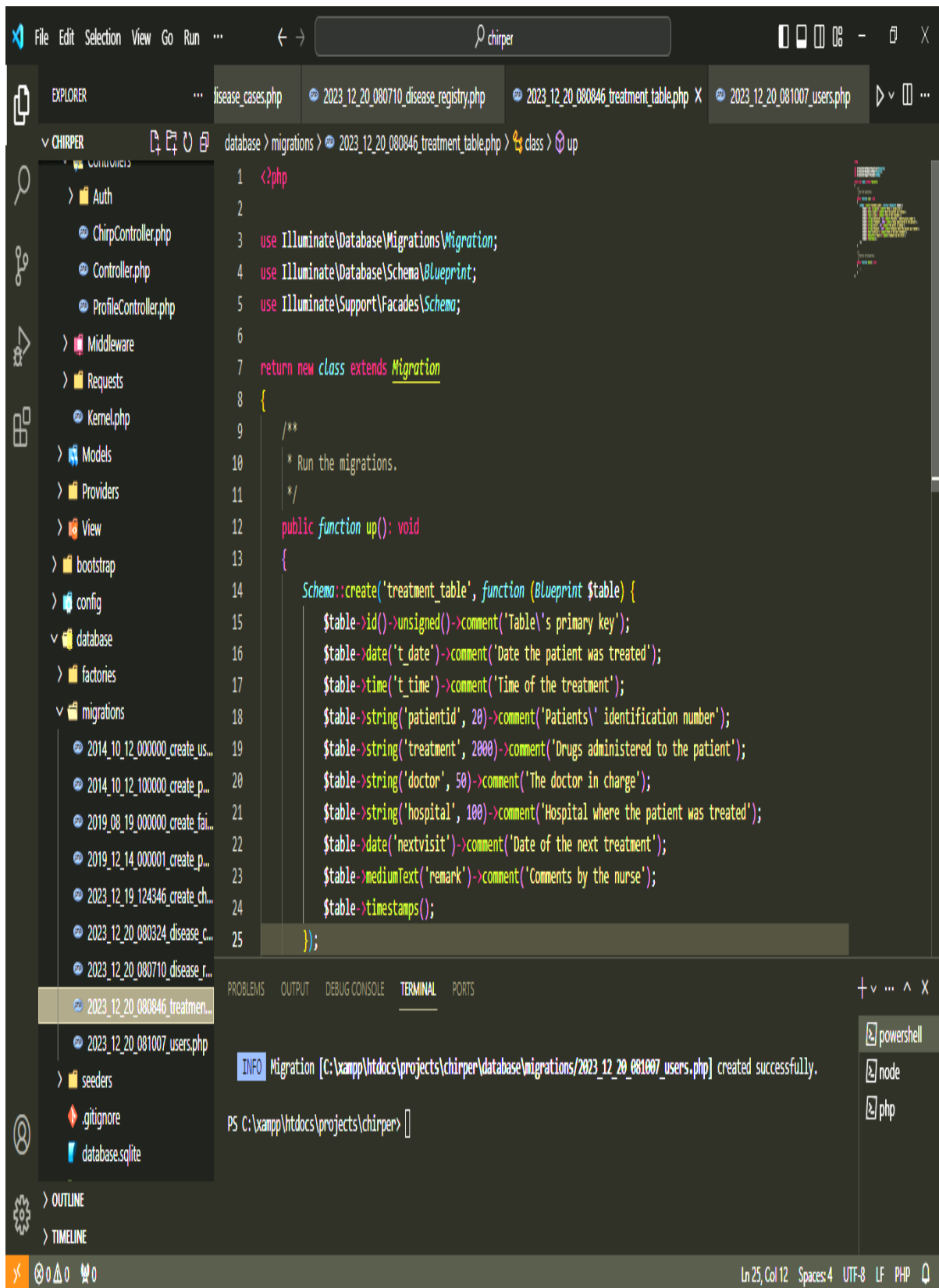


Figure 9. Migration file for creating the treatment table

C3 Source Code for Creating Ontology Database Using Laravel Migration Tool

```

<?php
use Illuminate\Database\Migrations\Migration;
use Illuminate\Database\Schema\Blueprint;
use Illuminate\Support\Facades\Schema;
return new class extends Migration
{
    /**
     * Run the migrations.
     */
    public function up(): void
    {
        Schema::create('disease_registry', function
(Blueprint $table) {
            $table->id()->unsigned()->comment('Table
primary key');
            $table->string('disease', 500)->comment('Disease
name');
            $table->string('symptoms', 5000)-
>comment('Disease symptoms');
            $table->string('type', 100)->comment('Disease
type');
            $table->string('treatment', 5000)-
>comment('Recommended treatment');
            $table->string('gender', 50)->comment('The sex
most affected by the disease');
            $table->string('agegroup', 30)->comment('The age
group most affected by the disease');
            $table->timestamps();
        });
    }
    /**
     * Reverse the migrations.
     */
    public function down(): void
    {
        Schema::dropIfExists('disease_registry');
    }
};

```

C4. Machine Learning Approach

C4.1 Disease Prediction: A Machine Learning Approach

The primary goal of the data analytics in this study is to develop a predictive model for the early detection of diseases based on the various symptoms and also to determine the accuracy and precision of our disease predictions.

C4.2 Model Training, Prediction and Evaluation

We trained a Classification model and made predictions on the three hundred and forty nine (349) dataset named “Disease Symptoms and Patient Profile Dataset” which was sourced from Kaggle.com and is titled "xAPI-Edu-Data.csv." The dataset was contributed by Kaggle user "LAKSIKA THARMALINGAM". It can be accessed at:

(<https://www.kaggle.com/datasets/uom190346a/disease-symptoms-and-patient-profile-dataset>).

80% of the dataset was used for training of our model while 20% was used for the testing. We were able to compute and print the confusion matrix along with various evaluation metrics, and plotted the confusion matrix for visual inspection of the model's performance. The evaluation metrics include accuracy, precision, recall, and F1 score.

We tested our dataset with three classifiers, Logistic regression, Decision tree and Random forest. Random forest recorded the best in terms of the Accuracy with 83%, 79% Precision and 80% Recall as shown in figure 10 below.

```

142
143 forest = RandomForestClassifier()
144 forest.fit(X_train, y_train)
145 forest_pred = forest.predict(X_test)
146 # Call the confusion matrix method
147 name = "Random Forest"
148 cm = confusion_matrix(y_test, forest_pred)
149 accuracy = accuracy_score(y_test, forest_pred)
150 precision = precision_score(y_test, forest_pred, pos_label=1)
151 recall = recall_score(y_test, forest_pred, pos_label=1)
152 f1 = f1_score(y_test, forest_pred)
153 evaluationArray = {"Accuracy": accuracy, "Precision": precision, "Recall": recall, "F1": f1_score}
154 print(name)
155 print(evaluationArray)
156 """Random Forest
157 {'Accuracy': 0.8285714285714286, 'Precision': 0.7931034482758621,
158  'Recall': 0.8846153846153846, 'F1': <function f1_score at 0x000001AD2037F1F0>} """
159 print(cm)
160 class_labels = ["Negative", "Positive"]
161 confMatrix(class_labels, name)
162
163 tree = DecisionTreeClassifier()
164 tree.fit(X_train, y_train)
165 tree_pred = tree.predict(X_test)
166 # Call the confusion matrix method
167 name = "Decision Tree"
168 cm = confusion_matrix(y_test, tree_pred)
169 accuracy = accuracy_score(y_test, tree_pred)
170 precision = precision_score(y_test, tree_pred, pos_label=1)
171 recall = recall_score(y_test, tree_pred, pos_label=1)
172 f1 = f1_score(y_test, tree_pred)
    
```

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Figure 10. Evaluation of trained models.

IV. DISCUSSION OF RESULTS

The result of this paper was achieved with the introduction of the Laravel migration schema tool for creating an ontology-based database. We developed an enhanced medical intelligence process that is very agile in predicting diseases and their symptoms when the model is queried. To determine the performance of our model in predicting diseases, we evaluated our datasets with three classifiers, and the result is as follows: With 84% Accuracy, 83% Precision, and 85% Recall, Random Forest produced the best results, outperforming findings from previous studies. Decision tree recorded 75% accuracy, 71% precision and 82% recall while Logistic regression 79% accuracy, 68% precision and 68% recall.

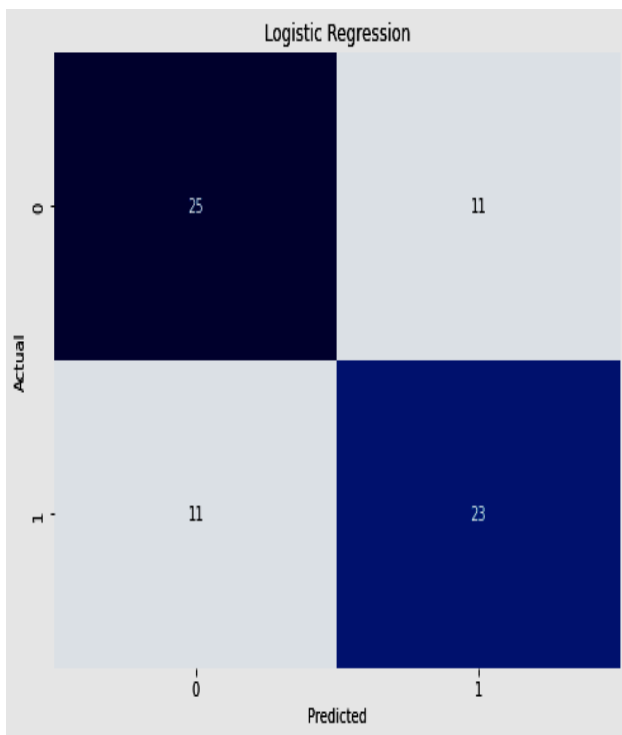


Figure 11. Confusion Matrix evaluation of the Logistic Regression

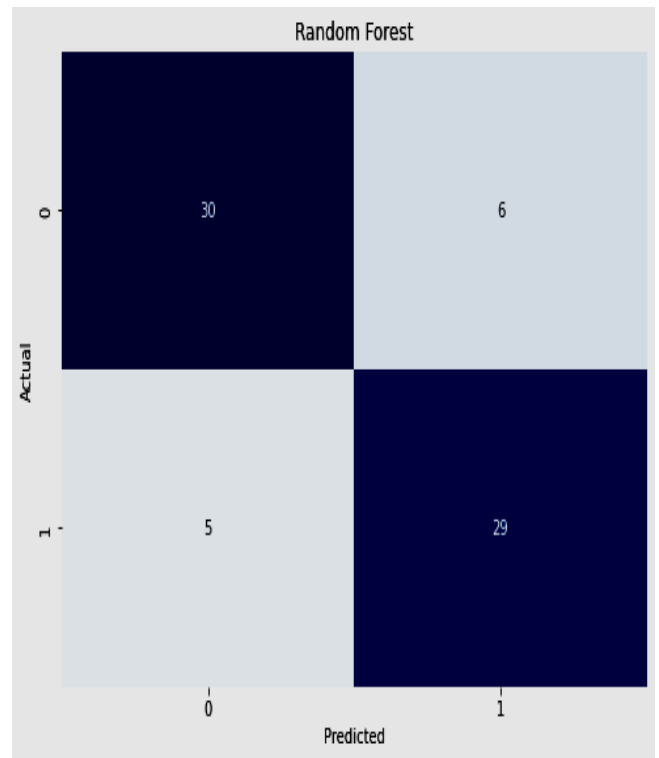


Figure 12. Confusion matrix evaluation of the Random Forest model

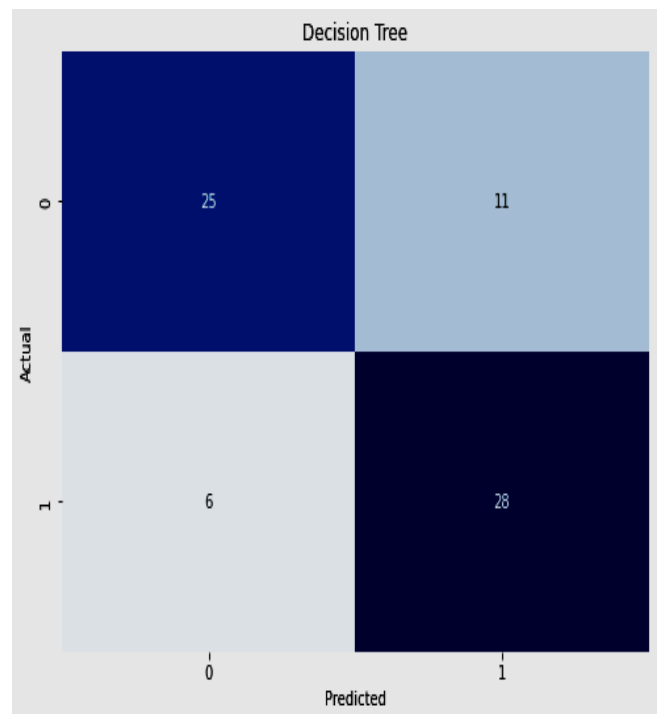


Figure 13. Confusion matrix evaluation of the Decision Tree model

Summary of the Models Evaluation:

TABLE I. SUMMARY OF EVALUATION OF THE MODELS

Model	Accuracy	Precision	Recall
Logistic Regression	0.685714	0.676470	0.676470
Decision Tree	0.757142	0.717948	0.823529
Random Forest	0.842857	0.828571	0.852941

V. CONCLUSION AND FUTURE WORK

Techniques such as Virtual Data Integration, a hybrid of Virtual Data Integration and Ontology-based has been done in the past with some challenges identified. However, there is need to search for an enhanced medical process with more efficiency and accuracy. This research work started by providing an overview of Ontology-based technique in a medical process and its benefits to the real-world of healthcare.

To develop an efficient medical intelligent process model, we reviewed some reports of existing literatures and studies and identified research gaps which strengthened our choice of Ontology-based technique for our research.

We used Laravel-migration tool for the Ontology database creation and Machine Learning with Python IDE to train and test our data set for the model developed.

As our main contribution, we introduced Laravel-migration for the creation of Ontology-based database which allows for quick access to the database and integration with other application. Confusion Matrix was used to determine the accuracy and the reliability of our model. Our result shows a 84% accuracy using random forest classifier.

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