A PROJECT REPORT

ON

AN EXPERT SYSTEM FOR SELECTING WART TREATMENT METHOD

submitted in partial fulfilment of the requirement for the degree of

BACHELOR OF TECHNOLOGY
IN
INFORMATION TECHNOLOGY

BY

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CERTIFICATE

This is certify that the project
entitled

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in partial fulfillment of the requirements for the award of the **Degree of Bachelor of Technology** in **Discipline of Engineering** is a bona fide record of the work carried out under our guidance and supervision at School of Computer Science, KIIT, deemed to be University, Bhubaneswar.

Date: 30/04/2018

(Prof. Divya Kumari)
Project Guide

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ABSTRACT

As benign tumors, warts are made through the mediation of Human Papillomavirus (HPV) and may grow on all parts of body, especially hands and feet. There are several treatment methods for this illness. However, none of them can heal all patients. Consequently, physicians are looking for more effective and customized treatments for each patient. They are endeavoring to discover which treatments have better impacts on a particular patient. The aim of this study is to identify the appropriate treatment for two common types of warts (plantar and common) and to predict the responses of two of the best methods (immunotherapy and cryotherapy) to the treatment. The study on which this project is based was conducted on 180 patients, with plantar and common warts, who had referred to the dermatology clinic of Ghaem Hospital, Mashhad, Iran. In this study, 90 patients were treated by cryotherapy method with liquid nitrogen and 90 patients with immunotherapy method. The selection of the treatment method was made randomly. A fuzzy logic rule-based system was proposed and implemented to predict the responses to the treatment method. It was observed that the prediction accuracy of immunotherapy and cryotherapy methods was 83.33% and 80.7%, respectively. The aim of this project is to improve this accuracy using machine learning algorithms. According to the results obtained, the benefits of this expert system are multifold: assisting physicians in selecting the best treatment method, saving time for patients, reducing the treatment cost, and improving the quality of treatment.

Contents

Chapter 1

Introduction

Machine learning and data mining algorithms are utilized to analyze large datasets and discover and extract knowledge from them. They are also employed as a tool in medical sciences, crime detection, risk assessment, and sales of products. These algorithms can analyze data in order to discover the unknown patterns in large databases. Industries such as banking, insurance, health, and marketing commonly apply them in order to reduce costs, improve the quality of research, and increase the amount of sales.

Classification is one of the important tasks in machine learning and data mining. Fuzzy rule-based systems have recently been employed for classification to handle the concept of partial truth. Truth values may range between completely false and completely true.

Fuzzy rule-based systems are applied in many different fields, including artificial intelligence, control theory and medical fields. In the medical field, they are utilized for the early diagnosis of diseases and important factors influencing them. In medical research, one of the most important fields is skin disease, and among the skin diseases, researchers generally apply machine-learning methods to Melanoma treatment. Melanoma is a type of skin cancer developing from melanocytes which is a type of pigment-containing cells. A number of studies have been performed on other skin diseases, using machine-learning algorithms. However, as far as we know, there has been no machine-learning research conducted in the field of wart treatment thus far. Although there are different wart treatment methods, physicians have not recognized which one is more effective for each patient. They are obliged to test each method individually.

In the given research, investigation of immunotherapy with candida antigen and cryotherapy with liquid nitrogen on 180 patients with plantar and common warts who had referred to the dermatology clinic of Ghaem Hospital, Mashhad, Iran has been conducted. These two treatment methods were selected as they are two of the best wart treatment methods. Cryotherapy is the most common wart treatment method. However, a number of difficulties arise when applying this method. The first problem is that it has side effects. Second, it is painful, and all the warts must be treated together. Third, many treatment sessions are required. Accordingly, experts are looking for novel ways to treat this issue. Immunotherapy is a new treatment method which has lately been employed. Fortunately, it lacks the majority of the deficiencies cryotherapy has encountered. In the present study, we propose a fuzzy rule-based algorithm to detect which one of these two treatment methods has better results for each patient. Not only do we aim to find a good classifier, but we also recommend some useful and interpretable rules to physicians so as to assist them in treating their patients. This diagnosis would help these patients spend less time and money. To the best of our knowledge, our study is the first one conducted in the domain of wart treatment.

Chapter 2

Literature Review

1. A fuzzy rule based expert system for stock evaluation and portfolio construction: An application to Istanbul Stock Exchange

The aim of this study is to construct appropriate portfolios by taking investor's preferences and risk pro- file into account in a realistic, flexible and practical manner. In this concern, a fuzzy rule based expert system is developed to support portfolio managers in their middle term investment decisions. The proposed expert system is validated by using the data of 61 stocks that publicly traded in Istanbul Stock Exchange National-100 Index from the years 2002 through 2010. The performance of the proposed system is analyzed in comparison with the benchmark index, Istanbul Stock Exchange National-30 Index, in terms of different risk profiles and investment period lengths. The results reveal that the performance of the proposed expert system is superior relative to the benchmark index in most cases. Additionally, in parallel to our expectations, the performance of the expert system is relatively higher in case of risk averse investor profile and middle term investment period than the performance observed in the other cases.

2. Hierarchical fuzzy rule based classification systems with genetic rule selection for imbalanced data-sets

In many real application areas, the data used are highly skewed and the number of instances for some classes are much higher than that of the other classes. Solving a classi- fication task using such an imbalanced data-set is difficult due to the bias of the training towards the majority classes. The aim of this paper is to improve the performance of fuzzy rule based classification systems on imbalanced domains, increasing the granularity of the fuzzy partitions on the boundary areas between the classes, in order to obtain a better separability. We propose the use of a hierarchical fuzzy rule based classification system, which is based on the refinement of a simple linguistic fuzzy model by means of the extension of the structure of the knowledge base in a hierarchical way and the use of a genetic rule selection process in order to get a compact and accurate model. The good performance of this approach is shown through an extensive experimental study carried out over a large collection of imbalanced data-sets.

3. Multimodal data and machine learning for surgery outcome prediction in complicated cases of mesial temporal lobe epilepsy

This study sought to predict postsurgical seizure freedom from pre-operative diagnostic test results and clinical information using a rapid automated approach, based on supervised learning methods in patients with drug-resistant focal seizures suspected to begin in temporal lobe. Method: We applied machine learning, specifically a combination of mutual information-based feature selection and supervised learning classifiers on multimodal data, to predict surgery outcome retrospectively in 20 presurgical patients (13 females; mean age7SD, in years 3379.7 for females, and 35.379.4 for males) who were diagnosed with mesial temporal lobe epilepsy (MTLE) and subsequently underwent standard anteromedial temporal lobectomy. The main advantage of the present work over previous studies is the inclusion of the extent of ipsilateral neocortical gray matter atrophy and spatiotemporal properties of depth electrode-recorded seizures as training features for individual patient surgery planning. Results: A maximum relevance minimum redundancy (mRMR) feature selector identified the following features as the most informative predictors of postsurgical seizure freedom in this study’s sample of patients: family history of epilepsy, ictal EEG onset pattern (positive correlation with seizure freedom), MRI-based gray matter thickness reduction in the hemisphere ipsilateral to seizure onset, proportion of seizures that first appeared in ipsilateral amygdala to total seizures, age, epilepsy duration, delay in the spread of ipsilateral ictal discharges from site of onset, gender, and number of electrode contacts at seizure onset (negative correlation with seizure freedom). Using these features in combination with a least square support vector machine (LS-SVM) classifier compared to other commonly used classifiers resulted in very high surgical outcome prediction accuracy (95%). Conclusions: Supervised machine learning using multimodal compared to unimodal data accurately predicted postsurgical outcome in patients with atypical MTLE.

4. Prediction of recombinant protein overexpression in Escherichia coli using a machine learning based model (RPOLP)

Recombinant protein overexpression, an important biotechnological process, is ruled by complex biological rules which are mostly unknown, is in need of an intelligent algorithm so as to avoid resource intensive lab-based trial and error experiments in order to determine the expression level of the recombinant protein. The purpose of this study is to propose a predictive model to estimate the level of recombinant protein overexpression for the first time in the literature using a machine learning approach based on the sequence, expression vector, and expression host. The expression host was confined to Escherichia coli which is the most popular bacterial host to overexpress recombinant proteins. To provide a handle to the problem, the overexpression level was categorized as low, medium and high. A set of features which were likely to affect the overexpression level was generated based on the known facts (e.g. gene length) and knowledge gathered from related literature. Then, a representative sub-set of features generated in the previous objective was determined using feature selection techniques. Finally, a predictive model was developed using random forest classifier which was able to adequately classify the multi-class imbalanced small dataset constructed. The result showed that the predictive model provided a promising accuracy of 80% on average, in estimating the overexpression level of a recombinant protein.

5. A new machine learning approach for predicting the response to anemia treatment in a large cohort of End Stage Renal Disease patients undergoing dialysis

Recombinant protein overexpression, an important biotechnological process, is ruled by complex biological rules which are mostly unknown, is in need of an intelligent algorithm so as to avoid resource intensive lab-based trial and error experiments in order to determine the expression level of the recombinant protein. The purpose of this study is to propose a predictive model to estimate the level of recombinant protein overexpression for the first time in the literature using a machine learning approach based on the sequence, expression vector, and expression host. The expression host was confined to Escherichia coli which is the most popular bacterial host to overexpress recombinant proteins. To provide a handle to the problem, the overexpression level was categorized as low, medium and high. A set of features which were likely to affect the overexpression level was generated based on the known facts (e.g. gene length) and knowledge gathered from related literature. Then, a representative sub-set of features generated in the previous objective was determined using feature selection techniques. Finally, a predictive model was developed using random forest classifier which was able to adequately classify the multi-class imbalanced small dataset constructed. The result showed that the predictive model provided a promising accuracy of 80% on average, in estimating the overexpression level of a recombinant protein.

Chapter 3

Software Requirements

3.1 Python

Recommended System Requirements

- Processors:
  - Intel® Core™ i5 processor 4300M at 2.60 GHz or 2.59 GHz (1 socket, 2 cores, 2 threads per core), 8 GB of DRAM
  - Intel® Xeon® processor E5-2698 v3 at 2.30 GHz (2 sockets, 16 cores each, 1 thread per core), 64 GB of DRAM
  - Intel® Xeon Phi™ processor 7210 at 1.30 GHz (1 socket, 64 cores, 4 threads per core), 32 GB of DRAM, 16 GB of MCDRAM (flat mode enabled)
- Disk Space: 2 to 3 GB
- Operating systems: Windows® 10, macOS, and Linux

Minimum System Requirements

- Processors: Intel Atom® processor or Intel® Core™ i3 processor
- Disk space: 1 GB
- Operating systems: Windows 7 or later, macOS, and Linux
- Python versions: 2.7.X, 3.6.X
- Included development tools: conda, conda-env, Jupyter Notebook (IPython)
- Compatible tools: Microsoft Visual Studio, PyCharm
- Included Python packages: NumPy, SciPy, scikit-learn, pandas, Matplotlib, Numba, Intel® Threading Building Blocks, pyDAAL, Jupyter, mpi4py, PIP, and others.

Software

- PIP and NumPy: Installed with PIP, Ubuntu, Python 3.6.2, NumPy 1.13.1, scikit-learn 0.18.2
- PIP and NumPy: Installed with PIP, Ubuntu, Python 3.6.2, NumPy 1.13.1, scikit-learn 0.18.2
- Intel® Distribution for Python 2018

Modifications

- Scikit-learn: Conda-installed NumPy with Intel® Math Kernel Library (Intel® MKL) on Windows (PIP-installed SciPy on Windows contains Intel MKL dependency) Portability
- Black-Scholes on Intel Core i5 processor and Windows: PIP-installed NumPy and Conda-installed SciPy Availability.

Chapter 4

Implementation

In this two algorithms have been used to design the system:

1.Artificial Neural Network

2.K-Nearest Neighbor

Artificial Neural Network (Back Propagation):

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras.

Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding.

The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.
Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organisation: An ANN can create its own organisation or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

Code:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

dataset = pd.read_csv('Cryotherapy.csv')
X = dataset.iloc[:, 0:6].values
y = dataset.iloc[:, 6].values

from sklearn.cross_validation import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)

y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
cm

accuracy_score(y_test, y_pred)
```

K-Nearest Neighbor:

KNN has no model other than storing the entire dataset, so there is no learning required. Efficient implementations can store the data using complex data structures to make look-up and matching of new patterns during prediction efficient. Because the entire training dataset is stored, you may want to think carefully about the consistency of your training data. It might be a good idea to curate it, update it often as new data becomes available and remove erroneous and outlier data.

Making Predictions with KNN:

KNN makes predictions using the training dataset directly.

Predictions are made for a new instance (x) by searching through the entire training set for the K most similar instances (the neighbors) and summarizing the output variable for those K instances. For regression this might be the mean output variable, in classification this might be the mode (or most common) class value.

To determine which of the K instances in the training dataset are most similar to a new input a distance measure is used. For real-valued input variables, the most popular distance measure is Euclidean distance.
Euclidean distance is calculated as the square root of the sum of the squared differences between a new point (x) and an existing point (xi) across all input attributes j.

Euclidean Distance (x, xi) = sqrt (sum ((xj – xij) ^2))

Other popular distance measures include:

- **Hamming Distance**: Calculate the distance between binary vectors.
- **Manhattan Distance**: Calculate the distance between real vectors using the sum of their absolute difference. Also called City Block Distance.
- **Minkowski Distance**: Generalization of Euclidean and Manhattan distance.

There are many other distance measures that can be used, such as Tanimoto, Jaccard, Mahalanobis and cosine distance. You can choose the best distance metric based on the properties of your data. If you are unsure, you can

experiment with different distance metrics and different values of K together and see which mix results in the most accurate models.
Euclidean is a good distance measure to use if the input variables are similar in type (e.g. all measured widths and heights). Manhattan distance is a good measure to use if the input variables are not similar in type (such as age, gender, height, etc.).

The value for K can be found by algorithm tuning. It is a good idea to try many different values for K (e.g. values from 1 to 21) and see what works best for your problem.

The computational complexity of KNN increases with the size of the training dataset. For very large training sets, KNN can be made stochastic by taking a sample from the training dataset from which to calculate the K-most similar instances.

KNN has been around for a long time and has been very well studied. As such, different disciplines have different names for it, for example:

- **Instance-Based Learning**: The raw training instances are used to make predictions. As such KNN is often referred to as instance-based learning or a case-based learning (where each training instance is a case from the problem domain).
- **Lazy Learning**: No learning of the model is required and all of the work happens at the time a prediction is requested. As such, KNN is often referred to as a lazy learning algorithm.
- **Non-Parametric**: KNN makes no assumptions about the functional form of the problem being solved. As such KNN is referred to as a non-parametric machine learning algorithm.

KNN can be used for regression and classification problems.

Code:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

dataset = pd.read_csv('Cryotherapy.csv')
X = dataset.iloc[:, 0:6].values
y = dataset.iloc[:, 6].values

from sklearn.preprocessing import LabelEncoder, OneHotEncoder
labelencoder_X = LabelEncoder()
X[:, 0] = labelencoder_X.fit_transform(X[:, 0])
onehotencoder = OneHotEncoder(categorical_features = [0])
X = onehotencoder.fit_transform(X).toarray()

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

import keras
from keras.models import Sequential
from keras.layers import Dense

classifier = Sequential()
classifier.add(Dense(output_dim = 4, init = 'uniform', activation = 'relu', input_dim = 7))
classifier.add(Dense(output_dim = 4, init = 'uniform', activation = 'relu'))
classifier.add(Dense(output_dim = 1, init = 'uniform', activation = 'sigmoid'))
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

classifier.fit(X_train, y_train, batch_size = 10, epochs = 180)
y_pred = classifier.predict(X_test)

y_pred = (y_pred >= 0.5)
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)

corr=dataset.corr()
corr=(corr)
sns.heatmap(corr,annot=True)
```

Chapter 5

Results of the Project

Accuracy of KNN:

```
In [9]:  from sklearn.metrics import confusion_matrix, accuracy_score
         cm = confusion_matrix(y_test, y_pred)
         cm

Out[9]:  array([[ 8,  2],
                [ 0, 13]], dtype=int64)

In [10]: accuracy_score(y_test, y_pred)

Out[10]: 0.91304347826086951
```

Accuracy of ANN:

```
In [9]:  from sklearn.metrics import confusion_matrix, accuracy_score
         cm = confusion_matrix(y_test, y_pred)
         cm

Out[9]:  array([[ 8,  2],
                [ 0, 13]], dtype=int64)

In [10]: accuracy_score(y_test, y_pred)

Out[10]: 0.91304347826086951
```

Chapter 6

Conclusion and Future Work

A computational intelligence-based expert system was developed in this paper to select the best methods for wart treatment. In the core of the proposed expert system exists a fuzzy logic system which analyzes patients' information and generates recommendation. It was successfully applied for selecting the treatment methods using the rules generated from the real data. It was observed that this system can greatly and effectively reduce both the time and cost of treatment for patients. It was found that faster treatment with lower complications is achieved through applying this system.

In a near future work, the team is going to increase the number of patients in order to obtain more precise and accurate results. Furthermore, other methods of wart treatment will be investigated for the sake of comparison. In addition, alternative machine-learning and data-mining algorithms will be applied to achieve a higher accuracy for wart treatment prediction by different methods.

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