A HYBRID INTELLIGENT FORECASTING MODEL TO DETERMINE MALARIA TRANSMISSION

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A HYBRID INTELLIGENT FORECASTING MODEL TO DETERMINE MALARIA TRANSMISSION

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Abstract

Strategies for fighting infectious disease rely on vector control, transmission blocking and medical assistance. Malaria is an infectious disease. According to World Health Organization 200 to 300 million of people are being affected with malaria every year and about 3 million people face fatal death yearly (WHO, 2013). This sporadic occurrence of malaria diseases in human has pushed the need to develop computational approaches for predicting in advance the occurrence of malaria diseases. The need to forecast in advance the occurrence of malaria disease and its outbreak will be helpful to take appropriate actions by individuals, World Health Organizations and Government Agencies and its devastating impact will be reduced. This research work proposes a coupling of Support Vector Machine (SVM), with Fuzzy Logic System (FLS) to determine the rate of malaria transmission. An hybrid forecasting model will be developed by conjoining Support Vector Machine, with fuzzy logic system to form a single model called SVM-FLS. The hybridization is done in such a way that the unique features of Support Vector Machine and Fuzzy Logic System (SVM-FLS) are captured, and then the weakness of one is strengthened by the other. Monthly cross-sectional surveys between January 2012 and December 2015(4 years) of malarial incidences will be collected from sample health centers in Minna Metropolis, Nigeria. Monthly averages of rainfall, temperature and relative humidity altogether with monthly malaria incidences will be considered as input variables. The proposed SVM-FLS will be compared with other existing models like Artificial Neural Networks(ANN), Fuzzy Logic System(FLS) and also with Support Vector Machine(SVM) to check its robustness and viability. Their statistical analysis will be conducted and their results will be compared.

Keywords: Malaria, Support Vector Machine (SVM), Fuzzy Logic System (FLS), Artificial Neural Networks (ANN), Classification, Regression, Forecasting, Transmission

1. INTRODUCTION

One of the most important things in life is health. But several diseases affect the proper functioning of human's health. One of such common disease is malaria. Malaria is an infectious disease. According to World Health Organization 200 to 300 million of people are being affected with malaria every year and about 3 million people face fatal death yearly (WHO, 2014). Malaria is a major public health problem because virtually all humans are being diagnosed of malaria infections at one time or the other and its effects increases drastically and causes great harm to human life. About three billion people are at risk of infection in 109 countries. Each year, there are an estimated 250 million cases of malaria leading to approximately one million deaths, mostly in children under five years of age (WHO,2014). Malaria is caused by a parasite known as *Plasmodium* specie being transmitted by an *Anopheles mosquito*. The parasites invade the blood and causes adverse effect on the blood cells. Within 48 to 72 hours the parasites multiply inside the red blood cells and break open, infecting more red blood cells. The first symptoms usually occur between 10-14 days to 4 weeks after infection. Malaria parasites can also be transmitted from a mother to her unborn baby (congenitally), by blood transfusions and by sharing needles used to inject drugs (MDHIL, 2015). In some part of the world, malaria parasites have developed resistance to insecticides and antibiotics. In recent years, the malaria parasite has grown so entrenched and has developed resistance to so many drugs that the most potent strains can scarcely be controlled. This year malaria may strike up to a half billion people. (National Geographic Society, 2015).

Malaria transmission is site specific due to different climatic change of a region.

Temperature, rainfall, relative humidity fluctuations affects the life cycle of malaria parasite (Depinay, Mbogo, Killeen, Knols, Beier, Carlson, Dushoff, Billingsley, Mwambi, Githure , 2004).

Only in the past few years has malaria captured the full attention of aid agencies and donors. The World Health Organization has made malaria reduction a chief priority. Bill Gates, who has called malaria "the worst thing on the planet," has donated hundreds of millions of dollars to the effort through the Bill and Melinda Gates Foundation. The Bush Administration has pledged 1.2 billion dollars. Funds devoted to malaria have doubled since 2003. The idea is to disable the disease by combining virtually every known malaria-fighting technique, from the ancient (Chinese herbal medicines) to the old (bed nets) to the ultramodern (multidrug cocktails). At the same time, malaria researchers are pursuing a long-sought, elusive goal: a vaccine that would curb the disease for good.(National Geographic Society, 2015).

Conventionally, problems are being solved by writing programs to decode the tasks. But difficulty arises when there is a huge amount of data which is hard to understand and to interpret by humans. A typical example is malarial incidences. A huge amount of malaria incidences are captured every year and there are difficulties in forecasting in advance its future occurrence and analysis of its possible threats. So the need for a machine learning method arises. Such a machine processes the data and automatically finds structures in the data, i.e. learns. The knowledge about the extracted structure can be used to solve the problem at hand. Problems being solved by machine learning methods range from classifying observations, predicting values, structuring data (e.g. clustering), compressing data, visualizing data, filtering data, selecting relevant components from data, extracting dependencies between data components, modeling the data generating systems, constructing noise models for the observed data, integrating data from different sensors, using classification. Thus, machine learning focuses on prediction based on known properties learned from the trained data sets (Nilsson, 1998).

Malaria is fuzzy in nature because a patient may have this answer to malaria: Yes /no and Much/little/very little (mild/moderate/severe). Many symptoms of different patient may even overlap. A malaria patient may even have characteristics of other diseases. Medical problems, therefore, cannot be generalized and analyzed using imagination. An analytical program is desperately required to integrate this complex network of problems and devise individualized solutions (Onuwa, 2014).

The combination of two or more Computational Intelligence schemes as a single model is called Hybrid Computational Intelligence (HCI) and it is becoming increasingly popular. This increased popularity lies in the extensive success of hybrid systems in many real-world complex problems (Giovanni and Vincenzo, 2005). A key prerequisite for the merging of technologies is the existence of a "common denominator" to build upon (Symeonidis andMitkas, 2005). In this research, part of the "common denominator" for the Support Vector Machines (SVM) hybridization of Fuzzy Logic System (FLS) is the inference procedures they deploy and their excellent predictive capabilities.

There are three main climatic factors that directly affect malaria transmission. They are *temperature*, *rainfall* and *relative humidity*. Several non-climatic factors, such as human/behavioural factors can also affect the pattern of malaria transmission and the severity of the problem.

2. LITERATURE REVIEW

According to World Health Organization in 2013, there are 97 countries and territories with ongoing malaria transmission, and 7 countries in the prevention of reintroduction phase, making a total of 104 countries and territories in which malaria is presently considered endemic. Globally, an estimated 3.4 billion people are at risk of malaria. WHO estimates that 207 million cases of malaria occurred globally in 2012 (uncertainty range 135–287 million) and 627 000 deaths (uncertainty range 473 000–789 000). Most cases (80%) and deaths (90%) occurred in Africa , and most deaths (77%) were in children under 5 years of age(WHO, 2013).

In India, 15,000, 000 to 20,000,000 approximately are confirmed cases of malaria yearly. So also malaria is a major public health challenge in our country, Nigeria (MDHIL, 2014). In Nigeria, on the average, each Nigerian suffers at least two or more attacks of malaria every year. Although millions recover, hundreds of thousands are not so lucky. Malaria accounts for about 60 percent of outpatient visits and 30 percent of hospitalizations; 25 percent of deaths in children under one year old; and 11 percent of maternal deaths a heavy burden on Nigerian families, communities, health system, and workforce (Sola and Chioma, 2010).

An early-warning system for malaria epidemics in Punjab based on rainfall, fever-related deaths and wheat prices was developed (Christophers,1911). Since that initial system, researchers and practitioners have continued to search for determinants of temporal and spatial variability of malaria to improve systems for forecasting disease burden. Malaria forecasting is now being conducted in many countries and typically uses data on environmental risk factors, such as climatic conditions, to forecast malaria incidence for a specific geographic area over a certain period of time.(Kate, Aman, Katia, Timothy, John, Zhuoyu and David 2013)

Mathematical, statistical and computational engineering models are playing a most valuable role in shedding light on the problem and for helping make decisions. Over the years, a vast number of approaches have been proposed looking at the problem from different perspectives. These encompass three general categories (see Fig. 1): (1) statistical methods for surveillance of outbreaks and identification of spatial patterns in real epidemics, (2) mathematical models within the context of dynamical systems (also called state-space models) used to forecast the evolution of a “hypothetical” or on-going epidemic spread, and (3) machine learning/ expert methods for the forecasting of the evolution of an ongoing epidemic. For all three of these categories there are again different approaches weaving a big and diverse literature.

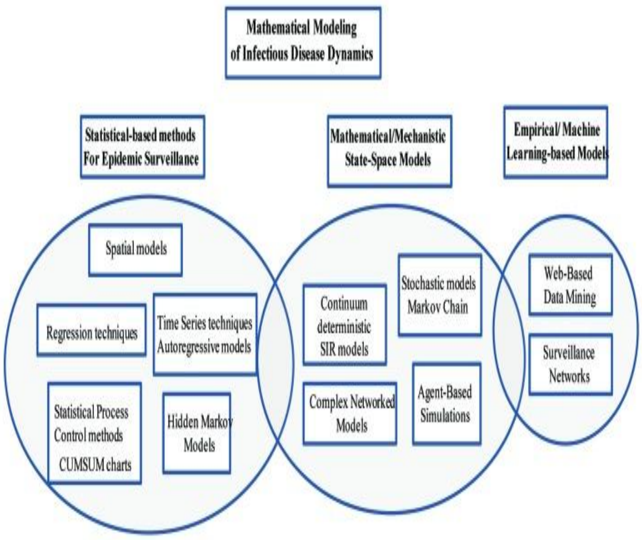

Fig 1: An Overview Of Mathematical Models For Infectious diseases (Constantinos & Lucia,,2013)

2.1 Statistical-Based Methods for Epidemic Surveilance

One of the most important aspects in epidemics revolves around the surveillance, early detection of possible outbreaks and patterns that may help controlling a spread. One of the very first success stories in the area is the modeling of cholera epidemic that swept through London in 1854. At that time John Snow, a physician, collected spatiotemporal data and by visualizing them in a map found that there was a particular pattern around the Broad Street water pum which actually was the zero point of transmission (McLeod, 2000). His analysis helped eradicate the disease. In the dawn of 20th century Greenwood an epidemiologist and statistician was the first Professor of Epidemiology and Statistics at the London School of Hygiene and Tropical Diseases establishing a rigorous mathematical connection between fields (Greenwood, 1916)

Today, global initiatives to combat epidemics require effective domestic action mechanisms and preparedness through the globe. An intensive worldwide effort led by World Health Organization and Centers for Disease Control is speeding up the developments for the establishment of a global surveillance network. New emerged pandemics such as the AIDS, the Severe Acute Respiratory Syndrome (SARS) of 2002–2003 and the H1N1 swine flu of 2009 pandemics reminds us about the importance of surveillance and prompt outbreak detection. Toward this aim, statistical methods have enhanced our potential in fighting epidemics allowing for rapid assessment of emerging situations. Obviously, the correctness of the data and the selection of the appropriate methodology are crucial for the construction of statistical models that can capture in an efficient robust way the communicable disease characteristics. To date, several statistical methods have been proposed (Unkel, Farrington, Paul, Garthwaite, Robertson, and Andrew 2012) for a review of statistical methods for the detection of disease outbreaks.

2.2 Mathematical State Space model

According to the level of the approximation of the reality and increasing complexity mathematical models may be categorized in the following categories:

"Continuum" models in the form of differential and/or (integro)-partial differential equations

Continuum models describe the coarse-grained dynamics of the epidemics in the population (Brauder, Castillo, 2001; Feng and, Dieckmann, 2006). One might, for example, study a model for the evolution of the disease as a function of the age and the time since vaccination or investigate the influence of quarantine or isolation of the infected part of the population(Hethcote, Zhien and Shenbing, 2002) Such models can be explored using powerful analysis techniques for ordinary or partial differential equations. However, due to the complexity and the stochasticity of the phenomena, most available continuum models are often only qualitative caricatures that cannot capture all of the details, therefore compromising epidemiological realism.

2.3 Empirical/ Machine Learning based Model

Recently, there is very rapid development of the use of machine learning. For instance machine learning is used in medical science to check health condition (Paokanta, Ceccarelli Scrichairatanakool, 2010; Martinez, Montero, Barbieri, Olivas, Mari, Sober, Amato, Lopez, Bassi, Beneddo, Stopper, Guerrero, andGatti, 2014) and diagnose a disease such as cancer (Kourou, T. Exarchos, P. Exarchos, Karanonzix, andFotiadis, 2014; Asadi, Dowling, YanandMitchell, 2014). In pharmacology ML find the right formula and reliable drugs to incapacitate a disease virus (R. Danger, I.S. Bedmar, P. Martinez, P. Rosso, 2010; Urquiza, Rojas, Pomares, Herrea, Florido, Valenzuela, andCeper, 2012). ML is also used to choose the effective therapeutic treatment (Caravaca, Olivas, Bataller, Serrano, Miquel, France andGurrero, 2013). Also ML can also be used in agriculture to increase agricultural production as with predicting pest plants (J. Patel, S. Shah, P. Thakkar andK. Kotecha, 2014). In the business world ML is used to predict the stock market and stock price index movement (J. Patel et al 2014).

2.31 Support Vector Machine (SVM)

Support Vector Machine is a well-known machine learning approach which has recently applied in the variety of fields such as computing, hydrology and environmental researches (Asefa, Kemblowski, McKee, Khalil, 2006; Ji, Sun, 2013, 1998; Mukkamala, Janoski, Sung, 2002)
It has mainly utilized in pattern recognition, forecasting, classification and regression analysis. It has been proved that its applications show superior performance compared to prior developed methodologies such as neural network and other conventional statistical models (Sung, Mukkamala 2003; Vapnik, Golowich, Smola, 1996; Huang, Davis, Townshend, 2002; Collobert, Bengio, 2000; Kasra, Shahaboddin, Chong, Muhammad, Dalibor, Sudheer (2014); Rajasekaran, Gayathri, andLee, 2008).

SVM are supervised machine learning in which the computer is presented with inputs and their desired outputs and the goal is to learn a general rule that maps inputs to outputs. (Nilson, 1998).
SVM is a machine learning model that focuses on prediction based on known properties (historical data) learned from the training data. **SVMs** are a set of related supervised learning (labeled training) data used for classification, recognizing patterns and regression analysis from a given data set.
SVM is based on the principle of statistical machine learning and structural risk minimization, which minimizes the upper bound generalization error compared to local training error, which is common technique in previously used machine learning methodologies [Vapnik,1998]. The mentioned technique proved advantages over other machine learning

algorithms.
Additional advantages provided in this methodology include: (1) applying high dimensional spaced set of kernel equations, which discreetly include non-linear transformation; thus, there is no assumption in functional transformation which makes data linearly separable indispensable and (2) unique solution due to the convex nature of the optimal problem(Kasra, Shahaboddin, Chong, Muhammad, Dalibor, andSudheer, 2014).

"There are a number of learning parameters that can be utilized in constructing SV machines for regression. The two most relevant are the insensitivity zone *e* and the penalty parameter *C*, which determines the trade-off between the training error and VC dimension of the model. Both parameters are chosen by the user.(Kecman, 2001)

2.32 Fuzzy Logic System(FLS)

Fuzzy Logic System is an intelligent system has become vital in the growth and survival of the healthcare sector. A good number of Fuzzy Logic expert systems have been developed to manage tropical diseases. An expert system was developed on tropical diseases to assist paramedical staff during training and in the diagnosis of many common diseases presented at their clinics. (Adekoya, Akinwale andOke, 2008). The system was flexible, friendly, and usable by people without much background in computer operations. The study concluded that the implementation of the system reduced doctors' workload during consultation and eased other problems associated with hospital consultations. A fuzzy expert system was designed for the management of malaria attempted to incorporate fuzzy techniques and develop a fuzzy expert system for the management of malaria. (Djam, Wajiga, Kimbi andBlamah, 2011). Also a decision-support model was designed for diagnosing tropical diseases using fuzzy logic (Olabiyisi, Omidiora, Olaniyan andDerikoma, 2011). In another related work, "cognitive analysis of multiple sclerosis utilizing fuzzy cluster means" was designed by (Imianvan andObi, 2012) where neuro solutions and crystal reports were used for neural network analysis and graphical representation to aid in the diagnosis of multiple sclerosis, which eliminates the challenges posed by the shortage of medical experts.

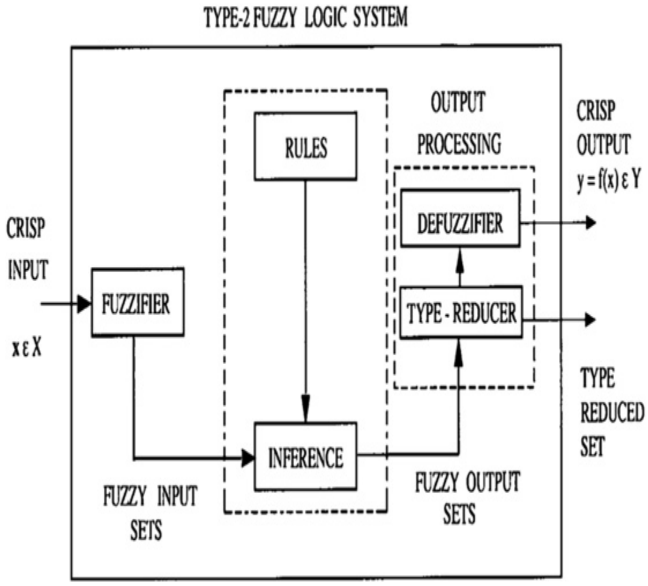

Fig. 1. 1. The structure of a Type-2 FLS (Mendel, 2003).

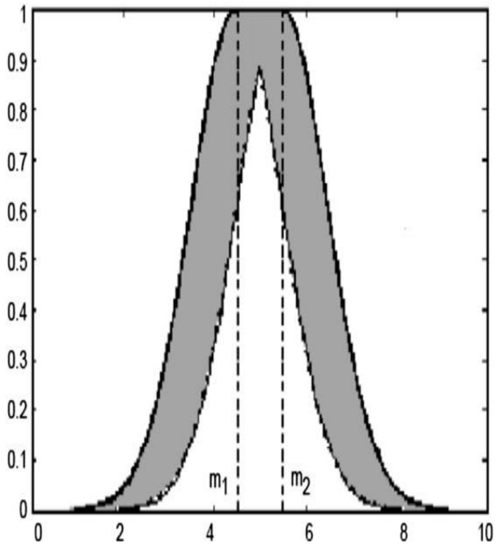

Fig.1. 2. Gaussian MF with uncertain mean (Mendel, 2003).

2.33 Type-1and Type 2 Fuzzy Logic System (FLS)

Type-1 Fuzzy Logic System (FLS) is the first established fuzzy logic system to deal with unambiguous or imprecise linguistic information. It is used to create an intelligent control and analyze complex problems.
Type-2 Fuzzy Logic System (FLS) was introduced as an extension of the concept of Type-1 FLS. Type-2 FLS has membership grades that are themselves fuzzy. For each value of a primary variable (e.g., pressure and temperature), the membership is a function (not just a point value). The secondary Membership Function (MF) has its domain in the (0, 1) interval. Hence, the MF of a Type-2 FLS is three dimensional, and it is the newly introduced third dimension that

provides new degrees of design freedom for handling uncertainties. Figs. 1 and 2 below show respectively the structure of a Type-2 FLS and Gaussian MF with uncertain mean. Further descriptions of the concepts of FLS, including Type-2 FLS and their applications can be found in (Wang, 2008; Castillo and Melin, 2008, Xing et al., 2008).

3. RESEARCH DIRECTION

The primary objective of this research is to develop a Support Vector Machine - Fuzzy Logic System (SVM-FLS) hybrid model to forecast in advance the occurrence of malaria disease. The model will serve as an intelligent hybrid system of higher performance and accuracy that will employ the unique features of the two methods (SVM and FLS) and complement the weakness of one with the strength of the other.

To achieve this objective we need to identify the threats, attacks and factors that contribute to being affected by malaria and the possible solutions. Due to the problem of malaria big data we need to develop a machine learning approach, a novel type of artificial neural network model called Support Vector Machine (SVM) to capture this big data and forecast in advance the rate of malaria transmission. Then capture the weaknesses of SVM and optimize it with Fuzzy Logic System (FLS). Finally, the functionality and robustness of the SVM-FLS hybrid model will be tested by comparing its statistical result with Artificial Neural Networks (ANN), Fuzzy Logic System (FLS) and Support Vector Machine (SVM) models.

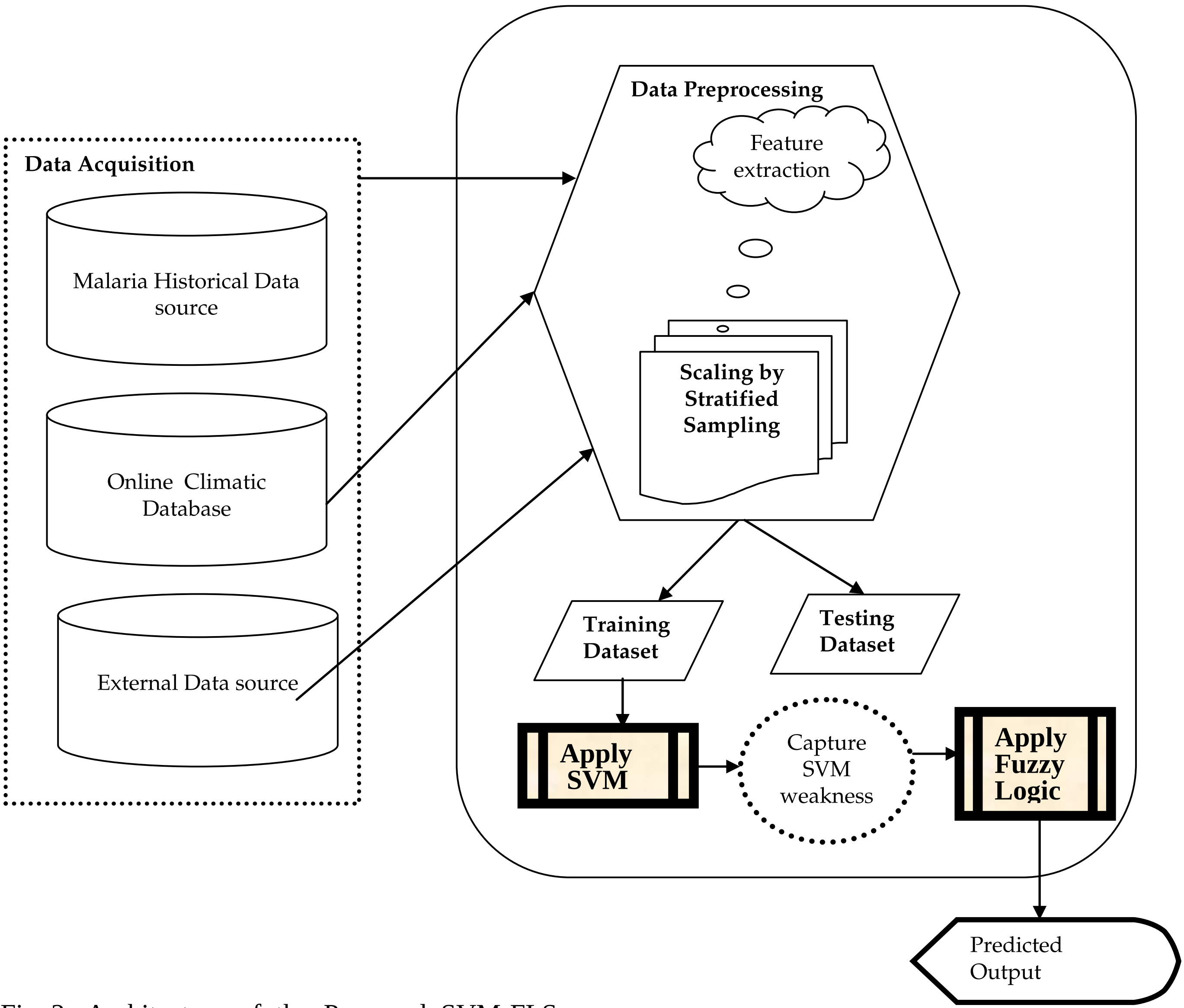

Fig 2. Architecture of the Proposed SVM-FLS Model for Malaria Prediction (Training Phase)

In the design framework of the SVM-FLS Model Framework for Malaria Prediction malaria data will be acquired from historical database of selected health centers. While the factors that contribute to having malaria such as rainfall, temperature and humidity data will be collected from online climatic database and other external sources. The features of these data will be extracted. Then we will use a stratified sampling technique to divide the dataset into training and testing dataset. The SVM-FLS architecture is divided into both training (Fig. 2) and testing phase (Fig. 3). At the training phase the training dataset will be mapped to the feature space. Then we apply SVM approach on the dataset. The weaknesses of the SVM approach will be captured and then optimize with FLS. At the testing phase the testing dataset will be used to test the robustness and functionality of the proposed SVM-FLS model.

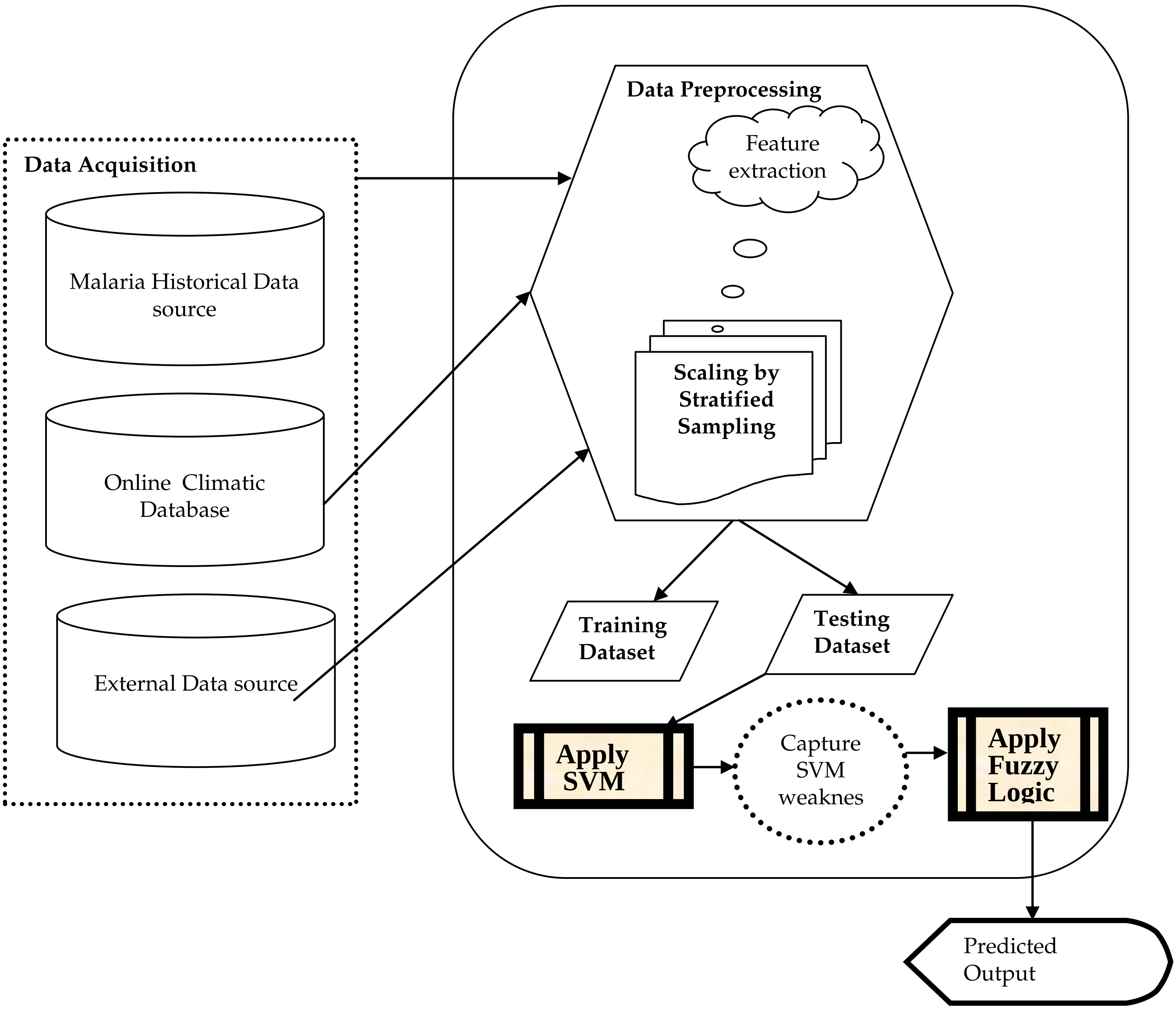

Fig 3. Architecture of the Proposed SVM-FLS Model for Malaria Prediction (Testing Phase)

4. CONCLUSION

Malaria has been a major public threat to human health. So the need to forecast in advance the occurrence of malaria disease so that it's devastating impact will be reduced is of great importance especially to the affected immense society. Support Vector machine (SVM) and Fuzzy Logic System (FLS) model is the nearest response to this call because it has the potential of combining human heuristics into computer assisted decision. In this paper, we have proposed an intelligent hybrid system of higher performance and accuracy that will employ the unique features of the Support Vector machine (SVM) and Fuzzy Logic System (FLS) models and complement the weakness of one with the strength of the other. SVM-FLS will provide a simple way to arrive at a definite conclusion from an imprecise and ambiguous medical data. And this will help individuals, World Health Organizations and Government Agencies to take appropriate actions. Contributions and Suggestions are welcome at this stage of the research.

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