International Journal of Innovative Research in Sciences and Engineering Studies (IJIRSES)

www.ijirses.com ISSN: 2583-1658 | Volume: 1 Issue: 2 | December 2021, pp. 1-8

A Bio-Informatics System for Intelligent Classification of Severity Index of Hypertension

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Abstract: *Hypertension, despite substantial advances in diagnosis and treatments, is still characteristically the leading cause of morbidity and mortality globally especially in Africa. This work examines state-of-the-art research solutions across the range of biomedical and health informatics on hypertension and then provides a contemporary and emerging algorithmic approach for intelligent classification. In order to optimize outcomes, machine learning (ML) techniques have the potential to improve the method of practice of cardiology services, mostly on early syndromic classification of hypertension. The work proposed a novel technique for training and testing of datasets to deduce and make clinical decisions. The research is powered by Artificial Intelligence (AI) approach using ML to optimize medical knowledge as a result of the increase of the measurements of complication levels from the data obtained, revealing clinically relevant evidence. An exploratory data analysis was done based on visualization of different variables to determine levels of parameter relationship with each other to enable informed, more accurate diagnosis, timely prognosis, and effective treatment planning supporting precision medicine regarding hypertension. Finally, a Support Vector Machine (SVM), was implemented for the classification of Severity Index (SI) of hypertension using clinical data obtained from University of Uyo Teaching Hospital (UUTH), Uyo, Nigeria. The findings indicate that, SVM gave 83% accuracy on classification. This shows efficiency in the classification of Severity index in Hypertension and also provide effective quality provisioning for medical practitioners and Healthcare departments in general.*

1. Introduction

Hypertension is a common ailment in today's world, and managing it is a difficult undertaking. It's been tough to even define the problem. The importance of certain Blood Pressure (BP) measurements in estimating risk is also debatable. With no well-defined cut points, effective management of hypertension necessitates the establishment of guidelines and thresholds, as well as treatment recommendations, for a condition that has shown a persistent and graded association to the risk of cardiovascular disease (CVD) [16]. Hypertension is a serious medical disorder that can jeopardize the health of your heart, brain, kidneys, and other organs. It is a leading cause of death in the globe, affecting 1 in every 4 men and 1 in every 5 women, affecting over a billion people. Low- and middle-income countries bear a disproportionate share of the burden of hypertension, Two-thirds of cases are found in those populations, owing to increased risk factors in recent decades. Hypertension, also known as high blood pressure (BP), is a global public health issue, according to the World Health Organization. This disease affects 1.1 billion individuals around the world, with two-thirds of them residing in low- and middle-income nations [20]. Furthermore, medical Proof suggests that early detection of hypertension, lifestyle changes, and strict control could help to limit the disease's progression and repercussions. Notwithstanding this, the vast majority of individuals with antihypertensive have no signs or warning signs, which is why it's known as the "silent killer."[13]. Nonetheless, due to an increase in publicly available datasets, the use of machine learning techniques in medicine has expanded in recent years. In recent years, Machine Learning (ML) methods have also been shown to perform well [9], [8] in the areas of diagnosis [15], clinical phenotyping [6], risk stratification [11], and treatment reaction prediction [3] because they provide an indiscriminate framework for choosing variables based on their effect on results severe hypertension, on the other hand, is rather frequent, with many individuals experiencing permanent or recurring increases. Given the massive cardiovascular dangers involved with this level of blood pressure increase, it is necessary to gain a better understanding of how these people are treated.

2. Literature Review

A. Basic Concepts in Hypertension

In order to contribute to the constant advancement in the field of medical sciences, [17] implemented an automated approach for the diagnosis and give possible recommendations using Fuzzy C Means (FCM) clustering techniques for high precision and reliable clinical supervision. FCM clustering algorithm is being

used as the problem solving and reasoning algorithm in the inference engine of the knowledge base system for the evaluation, classification and matching of patterns to more than one class of glaucoma. However, hypertension the prevalent chronic condition discovered by chance, is a substantial risk factor for both cerebrovascular and coronary heart disorders. High blood pressure (BP) is a key risk factor for heart and kidney disease [7]: [8]. There are two types of hypertensions: primary and secondary [4]. Although the exact origins of hypertension are unknown, it has been linked to a number of non-modifiable (such as age, race, and genetic makeup) and modifiable (such as being overweight/obese, salt and potassium intake, poor physical fitness, and excessive alcohol use) risk factors [21]. To prevent primary hypertension, population-based initiatives involving lifestyle changes can be used [22]. Nonetheless, hypertension is a major public health concern around the world. Information on the severity of hypertension-related disease is critical for designing effective preventive and control methods [10]. Hypertension, or increased blood pressure, is a condition in which the blood pressure increases to extremely high levels. Blood exerts an excess amount of pressure against the artery walls as the body's smallest blood capillaries (arterioles). Blood arteries in the kidneys, brain, and eyes may potentially be damaged. In contrast, blood pressure is the pressure of putting an emphasis: systolic blood. The systolic pressure (the larger pressure and the first number measured) is the pressure that blood exerts as the heart contracts to pump blood to the peripheral organs and tissues exerts on the artery walls. The leftover pulse on the arteries as the heart is at rest between beats is called diastolic pressure (the lower value). Hypertension is diagnosed when blood pressure reaches or surpasses 140/90 mmHg (140 millimetres of mercury over 90 millimetres of mercury).

B. Health Complications of Hypertension

When patients with hypertension check their blood pressure at home or at the pharmacy and the reading is high, they may become alarmed. It's uncommon for people with an isolated finding of high blood pressure to show up at their local emergency department, but in many situations, the main issue is the cumulative consequence of ongoing uncontrolled hypertension, not a single high reading. Heart failure, coronary artery disease, stroke, renal disease, peripheral artery disease, and hypertensive retinopathy, an eye illness, are all risks associated with high blood pressure [15]. Because hypertension is linked to type 2 diabetes, the United States has made it a priority to address the issue. A recommendation for diabetes screening in people with high blood pressure has been given by the Preventive Services Task Force. Blood pressure regulation leads to a rapid reduction in the risk of cardiovascular disease. The following are some of the health issues that might arise as a result of hypertension:

1. Heart and blood vessel problems

As the body adjusts to unusually high blood pressure, changes in the structure and operation of the heart and blood arteries culminate in hypertensive heart disease. Consider the heart as a pump working against a fluid circuit, and imagine how much more work it has to do as the pressure in the circuit rises. With the use of ACE inhibitor drugs, some of the alterations induced by persistent high blood pressure can be partially reversed. As a consequence of natural stress, hypertension causes wear and tear of essential organs and veins. Blood vessels have systems to regulate blood flow in the body, and when blood pressure rises, the blood vessels constrict. The walls of the blood vessels thicken over time, causing tissue injury and stiffening of the vessel walls.

2. Problems with the Eyes

Hypertensive retinopathy is the term for hypertensive eye disease. Changes in the blood vessels in the retina of the eye eventually cause the vessel's integrity to be compromised, allowing blood or fatty acids to flow onto the sensitive retinal tissue. This causes lasting eyesight changes and is easily avoidable.

3. Stroke and Other Brain Issues

Stroke complications can occur as a result of a hemorrhage in the brain's blood vessels or, more commonly, as a result of poor blood flow through arteries weakened by persistently high blood pressure. 4 Ischemic strokes, or strokes caused by a lack of blood flow, account for about 85% of all strokes. Hypertensive encephalopathy is another indication of hypertension that affects the brain. Swelling in the brain induced by abnormalities in blood flow at very high blood pressure causes a change in mental status, which is frequently accompanied with headache and nausea. This condition is linked to hypertensive emergency or malignant hypertension.

4. Kidney Disease

Chronic high blood pressure is one of the most common causes of chronic renal disease, which often necessitates dialysis. The kidneys filter blood, and when the tiny blood arteries in the kidneys are damaged by uncontrolled chronic hypertension, the

body is unable to filter waste. People with renal impairment may require a kidney transplant or spend hours hooked up to dialysis machines that remove waste materials from their circulation. Preventing the complication is preferable and less complicated in any instance.

C. Artificial intelligence in Management of Hypertension

Artificial intelligence (AI) is a vast discipline of computer science concerned with a machine's ability to generate rational behavior based on external inputs. Artificial intelligence (AI) aims to develop systems that can execute activities that would otherwise necessitate the use of human intelligence. Virtual assistants, search prediction technologies, and even ride-hailing services are examples of Artificial Intelligence (AI) in everyday life. Reasoning (drawing conclusions based on facts), natural language processing (reading and understanding human languages), planning (capacity to operate independently and flexibly to design a series of activities to achieve a final goal), and Machine Learning (ML) are all components of an AI system (algorithms that improve automatically through experience). The phrases artificial intelligence (AI) and machine learning (ML) have been used interchangeably, however there is a difference between the two. To be able to distinguish between them. Artificial intelligence (AI) is a technology that allows a machine to mimic human behavior, while machine learning (ML) is a form of AI that allows software or algorithms to learn from prior data without having to train it directly. AI has a broad scope that includes learning, reasoning, and self-correction, but ML has a narrower scope that only includes learning and self correction when presented with new data. Because machine learning is at the heart of most AI applications in health care (ML). Machine Learning (ML) has been used to investigate some of the issues surrounding hypertension diagnosis and management, including hypertension prediction from clinical data and systolic blood pressure prediction (BP) from retinal fundal pictures [12] and estimation of absolute danger decrease in cardiovascular events by means of data from randomized medical trials.

3. Research Method

A. Methodology

An approach for solving a research topic analytically is referred to as "research methodology.". As a result, it is concerned with the investigation of many stages that a researcher might take in conducting research, as well as the processes that underpin them. The general research plan that specifies the way in which research will be conducted, among other things, identifies the methods to be employed, is known as research methodology. Publication research, surveys, and other research approaches, as well as current and historical data, may be used in the process. The procedures or strategies used to find, select, process, and analyze information about a topic are referred to as research methodology. A research methodology section allows the researcher to assess the overall validity and dependability of a study. The research methodology usually aids in the effective completion of a comprehensive system revision. This will aid in comprehending the current system's functionality in order to determine how the new system will be organized and the functions required to address the ostensibly existing problem. As a result, this study used a quantitative methodology based on data collected through a Machine Learning Model here which is Support Vector Machine (SVM).

B. Model Design

Today, AI enterprises are being implemented in a variety of businesses for a variety of uses. Predictive modeling, pattern recognition systems, automated vehicles, interactive systems, high energy activities, and goal-driven systems are examples of these applications. Each of these ventures has one thing in common: they're all based on an understanding of the business challenge and the need to apply data and machine learning algorithms to it, leading inside a machine learning model that meets the design specifications. A machine learning model is a computer program which has been trained to recognize specific patterns. We train the model on a set of data and give it an algorithm to use to reason about and learn from that data. Once the model has been trained, you can use it to reason over data it hasn't seen before and make predictions about it. Hence, the following steps aided in our model design in this research work;

i. Define our problem clearly (goal, expected outcomes, etc.).

ii. Obtain information (i.e., data).

iii. Select a metric for success.

iv. Determine the framework and the various procedures that are available.

v. Prepare the information (dealing with missing values, with categorical values).

vi. Correctly spill the info.

vii. Explain the differences between overfitting and underfitting, including what they are and how to avoid them.

viii. A brief description of how a model learns.

ix. What is regularization, and when should it be used?

x. Create a benchmarking model.

xi. Select an appropriate model and fine-tune it to achieve the best potential results.

C. Model Formulation with SVM

Today, Hypertension (HTN) outcomes can include serious complications, when the condition progresses to a critical stage. Hypertension is among the most frequent chronic human disorders, and major hypertensive problems can jeopardize a client's life and health, cause substantial damage to the heart, brain, and kidneys, among other organs. Because of the serious consequences, patients and doctors are working to prevent hypertension from developing and progressing. People must first properly estimate the severity index of occurrence and avoid them before they occur in order to effectively limit the incidence of consequences. However, because there are no evident early symptoms of hypertensive problems, detecting the threat of outcomes remains difficult. Hence, in this research, we have devised a way to model the Severity Index of Hypertension based on classification and prediction models for efficient medical diagnosis support based on machine learning approach. Furthermore, in order to perform Severity Index Classification, we employed Support vector machine (SVM) using R programming language. Different set of R scripts will be provided for the Classification. Support Vector Machines are powerful Machine Learning methods for Classification and Regression. When we wish to use it to solve a problem, the margin type we choose is crucial. Hence in this research we will apply the hard margin classifier reason being that our data is linearly separated into two classes (high or low severity index). In order to realize this, we will select the best hyperplane, i.e., the one with maximum margin with the lowest number of errors that will linearly separate our data into two distinct classes in order to achieve efficient throughput, suppose that perhaps the hyper- plane distinguishing our two classes is shown in eqn1 based on [2].

$$w^T x + b = 0 \quad (1)$$

The two classes are presented in figure 1.

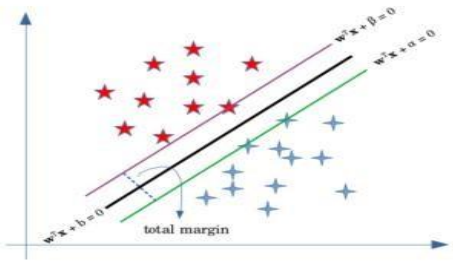

Fig 1 Total Margins Separated

Furthermore, the two margins can be defined my two separate parallel planes which is presented in the equation 2 and 3 respectively.

$$w^T x + \alpha = 0 \quad (2)$$

$$w^T x + \beta = 0 \quad (3)$$

In a diagram 1, these are the purple and green lines, we aim to optimize the separation between the two hyperplanes while avoiding any misclassifications in the hard margin SVM. The algorithm for the distances of a point from a plane can be used to calculate this distance. As a result, the distance between the blue and red spots and the black line would be: and; so, the overall range would be: As a result, in order for us to optimize this profit margin:

$$\frac{|W^T + \alpha|}{||w||} \quad (4)$$

and;

$$\frac{|W^T + \beta|}{||w||} \quad (5)$$

Hence, the total margin would become:

$$\frac{|\alpha - \beta|}{||w||} \quad (6)$$

Hence in other for us to maximize this margin. We can think about and examine without losing generality $= b + 1$ and $\beta = b - 1$. The challenge then becomes one of maximization or minimization, $\frac{2}{||w||}$ or minimize $\frac{2}{||w||}$. We'll work with the squared version of the issue, which is shown in equation 8, to make calculating the gradients easy.

$$\min_{w,b} \frac{1}{2} ||w||^2 \equiv \min_{w,b} \frac{1}{2} w^T w \quad (7)$$

Furthermore, on the aspect of prediction we adopted a logistic regression model for predicting hypertension severity index based on five parameters which are Sugar level (FBS), Cholesterol, Age, gender and Body Mass Index (BMI). As a result, linear classification is a

method of classifying data using a linear prediction function and associating weights with dependent variable values. This method could include non-linear operations.

D. Algorithm for Support Vector Machine

i. Step 1: Read in the in the CSV data file

ii. Step 2: Display the structure of the data.

iii. Step 3: Summarized the data.

iv. Step 4: Plot data

v. Step 5: Checked whether there are any abnormalities in the data.

vi. Step 6: Check for outliners in the data.

vii. Step 7: Convert the severity index column to a factored variable.

viii. Step 8: Create a two-way factor table for our severity index.

ix. Step 9: Data Slicing in the ratio of 80:20 %.

x. Step 10: We train our model with the training set as splitted in 11.

xi. Step 11: Summarized the model

xii. Step 12: Supply the test data into the model for Classification xiii.

xiii. Step 13: Supply the train data into the model for Classification xiv.

xiv. Step 14: Determine the accuracy of the model using the confusion matrix xv.

xv. Step 15: Check the percentage accuracy from our confusion matrix

E. Exploratory Data Analysis

Exploratory data analysis is a simple classification algorithm that is frequently performed visually. It is a method of evaluating data sets in order to describe their essential featurest. Every machine learning problem solving involves EDA. It's undoubtedly the most crucial aspect of any machine learning effort. Using charts and graphs, one may make sense of the data and determine whether or not there is a relationship. As a result, all findings were made using these numerous graphs. Therefore, Data visualization involves the graphical representation of information and data. Visualizations make it easy to identify and comprehend trends, outliers, and patterns in data by using visual components like graphs and maps. In the Big Data era, data visualization tools and technologies are crucial for analyzing massive amounts of data and making data-driven decisions. Nevertheless, the following visualizations were carried out from our data sets. Figure 2. depicts the visualization of how Age varies with the stage of hypertension.

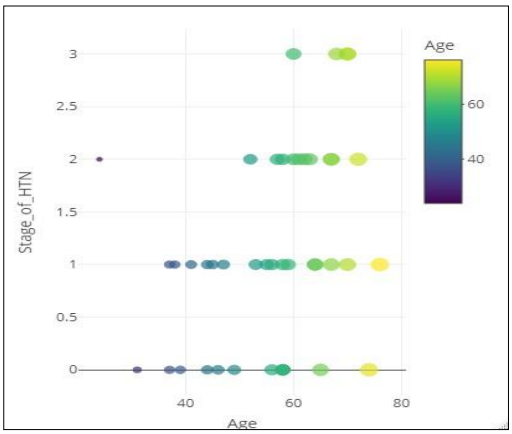

Fig 2. *Age vs Stage of HTN*

Again, Figure 3. depicts the visualization of Severity variation with Pulse pressure

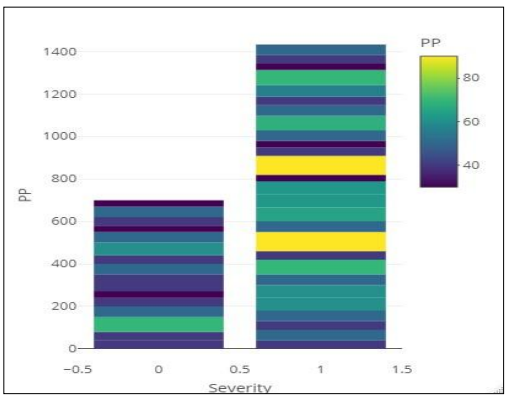

Fig 3. *Severity vs PP*

Again, Figure 4 and 5 depicts the visualization of how geographical region can have effect on both the stage of hypertension and the Severity index.

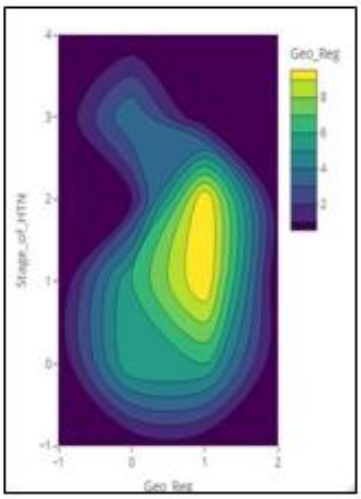

Fig. 4 *Geo_Reg vs Stage of HTN*

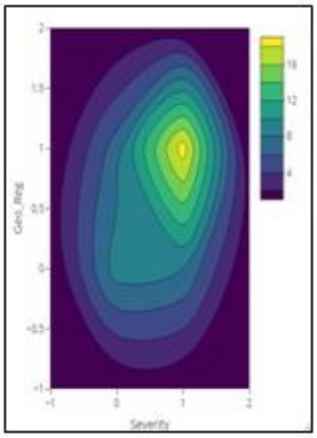

Fig. 5 *Severity Vs Geo_Reg*

Nevertheless, Figure 6 depicts the visualization of how Age varies with the Body mass index (BMI)

4. Results

Structured and objective assessment of an ongoing or completed research is called result evaluation. The task is to identify the knowledge of research achieving objectives, plan to transform, economy, impact, and durability. This research work adopted a Support vector machine Algorithms for classification and prediction of severity index of hypertension from a well-defined and structured dataset which was collected in the teaching hospital of the University of Uyo, Akwa Ibom sate, Nigeria Consequently, before use our dataset in our model we explore the structure of our data set with all parameters.

Figure 6.0 shows a schematic structure of our dataset.

```
data.frame':   31 obs. of  20 variables:
$ Age                 : int  37 65 74 64 58 55 63 44 70 70 ...
$ Gender              : int  0 0 0 1 1 1 1 0 0 1 ...
$ Geo_Reg             : int  1 1 1 0 1 0 1 1 0 1 ...
$ SP                  : int  120 110 90 120 130 130 140 130 180 135 ...
$ DP                  : int  70 70 50 60 70 80 70 90 90 70 ...
$ PP                  : int  50 40 40 60 60 50 70 40 90 65 ...
$ MAP                 : num  86.7 80.3 63.3 80 90 ...
$ Family_Hx           : int  1 0 0 0 1 1 0 0 1 1 ...
$ Sodium              : int  137 145 128 136 136 142 132 136 142 142 ...
$ Dur_of_HTN          : int  3 5 25 6 11 3 5 2 3 6 ...
$ Cholesterol         : num  3.2 5.3 3.3 3.5 5.1 3.5 3.4 3.1 3 3.2 ...
$ Stage_of_HTN        : int  1 0 0 1 1 1 2 1 3 1 ...
$ FBS                 : num  3.1 5.4 5.4 5.4 3.9 7.1 5.1 5 3.4 13.5 ...
$ Weight              : num  75 60 71 101 80.2 65 96 57 60 65 ...
$ Height              : num  1.62 1.55 1.72 1.58 1.64 1.64 1.79 1.65 1.57 1.66 ...
$ DM                  : int  0 0 1 0 0 1 1 0 0 1 ...
$ Duration_of_Control: int  2 4 23 4 5 2 2 1 3 3 ...
$ Alcohol             : int  0 0 0 0 0 0 0 0 0 0 ...
$ BMI                 : num  28.6 25 24 40.5 29.8 ...
$ Severity            : Factor w/ 2 levels "0","1": 2 1 1 2 2 2 2 2 2 2 ...
```

Fig 6.0 Structure of our SVM data frame

Nevertheless, we now supply our train dataset into SVM in order for us to build our training model hich we will use for our classification with new or dataset in R and the result is depicted in figure 7.

```
Support Vector Machines with Linear Kernel

31 samples
19 predictors
 2 classes: '0', '1'

Pre-processing: centered (19), scaled (19)
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 27, 28, 28, 28, 28, 28, ...
Resampling results:

  Accuracy   Kappa
  0.8333333  0.6

Tuning parameter 'C' was held constant at a value of 1
```

Fig 7 *SVM Build Model Result*

Furthermore, we now use our test data which was segmented from our overall dataset in ratio of 30% in order to test our train model and classify the severity index of each patient. This depicted in figure 8.

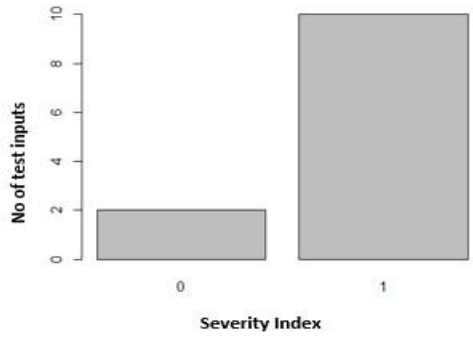

Fig 8 *SVM Result on test set*

Nevertheless, confusion matrix was adopted for the evaluation of the accuracy of our model. The confusion matrix depicts how our classification model becomes perplexed when making predictions. It reveals not only the number of errors produced by a classifier, but also the sorts of mistakes committed.

Table 1: Confusion Matrix Observed

Severity	Low (0)	High (1)
Low (0)	TP	TN
High (1)	FP	FN

Table: 2 Confusion Matrix for SVM

Severity	0	1
0	12	0
1	0	19

Hence, from our Classification data, our SVM model accuracy on training set is summaries in figure 9.

```
train_pred  0  1
         0 12  0
         1  0 19

               Accuracy : 1
                 95% CI : (0.8878, 1)
    No Information Rate : 0.6129
    P-Value [Acc > NIR] : 2.565e-07

                  Kappa : 1

 Mcnemar's Test P-Value : NA

            Sensitivity : 1.0000
            Specificity : 1.0000
         Pos Pred Value : 1.0000
         Neg Pred Value : 1.0000
             Prevalence : 0.3871
         Detection Rate : 0.3871
   Detection Prevalence : 0.3871
      Balanced Accuracy : 1.0000

       'Positive' Class : 0
```

Fig 9 *Accuracy of SVM based on test data*

5. Conclusion

In this research work, we have offered solutions for ensuring Effective and Resourceful Hypertension Severity Classification for Efficient Medical Diagnosis Support through the adoption of Machine Learning Approach. We have presented in this work a comprehensive review of the concepts of Hypertension, by highlighting the importance indicators for hypertension classification and support base, has it related to Hypertension Severity Management, its performance indicators or metrics that ensures Support base has regards to Hypertension Severity Management are as well considered. Although previous research and models in the area of Hypertension Management have been proposed progressively, but they have been numerous loop holes as regards the aspect of Severity index of hypertension Classification such has effective methodology to use, effective data and the realistic nature of the data, the accuracy level of the modelling algorithm are all and indication for quality-of-service (QoS) provisioning. Furthermore, we have also demonstrated possible solutions effectively that when applied would facilitate better Severity Index Classification of hypertensive patient for Quality of service (QoS) provisioning which will stand as a support medical parastatal. Meanwhile, a Machine learning approach which is Support Vector Machine (SVM) Model was adopted for the Classification of Severity Index of Hypertension. Additionally, we preprocessed our clinical field datasets, by undergoing data cleaning, and feature extraction in order or our data be used effectively in our machine learning model. Our data was divided in to training and test set in the ratio of 80:20% for train and test set. Our data was used to build and test our model, SVM gave us 83% accuracy on classification, SVM use 19 metrics for the classification.

Author Contributions: Conceptualization, I. Umoren;, Methodology, I. Umoren, Victoria Essie,; software, Victoria Essien, Imeh Umoren, Idongesit Umoh; validation, I. Umoren; formal analysis, Imeh Umoren, Victoria Essien; investigation, Victoria Essien.; resources, Idongesit Umoh, Victoria Essien; data curation, I. Umoren; Idongesit Umoh writing original draft preparation, Victoria Essien, I. Umoren,; writing review and editing, I. Umoren; Idongesit Umoh visualization: Victoria Essien, I. Umoren, Supervision, I. Umoren; Project administration, I. Umoren; Idongesit Umoh, Funding acquisition, I. Umoren. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: The authors would like to thank Department of Computer Science, Faculty of Physical Sciences, Akwa

Ibom State University, and University of Uyo Teaching Hospital (UUTH), Nigeria for the support during the research work.

References

[1] Adam Felman (2019). Everything you need to know about hypertension, medically reviewed by Brenda B. Spriggs, M.D., MPH, FACP.

[2] Akbar Karimi (2021). Using a Hard Margin vs. Soft Margin in SVM.

[3] Basu S, Raghavan S, Wexler DJ, Berkowitz SA (2018). Characteristics associated with decreased or increased mortality risk from glycemic therapy among patients with type 2 diabetes and high cardiovascular risk: machine learning analysis of the ACCORD trial. Diabetes Care. 41:604–612. doi: 10.2337/dc17-2252. [4] Carretero OA, Oparil S (2000). Essential hypertension. Part I: definition and etiology. Circulation, 101:329– 35.

[4] Deo RC (2015). Machine learning in medicine. Circulation. 132:1920–1930. doi: 10.1161/ CIRCULATIONAHA.115.001593.

[5] Ernande L, Audureau E, Jellis CL, Bergerot C, Henegar C, Sawaki D, Czibik G, Volpi C, Canoui-Poitrine F, Thibault H, (2017). Clinical implications of echocardiographic phenotypes of patients with diabetes mellitus.J Am Coll Cardiol.70:1704–1716.doi: 10.1016/j.jacc.2017.07.792.

[6] Forouzanfar MH, Liu P, Roth GA, Ng M, Biryukov S, Marczak L, (2017). Global burden of hypertension and systolic blood pressure of at least 110 to 115 mm Hg, 1990–2015. 317:165–82.

[7] Fujiyoshi A, Ohkubo T, Miura K, Murakami Y, Nagasawa SY, Okamura T l (2012). Blood pressure categories and long-term risk of cardiovascular

disease according to age group in Japanese men and women. Hypertens Res, 35:947–53.

[8] Goldstein BA, Navar AM, Carter RE (2017). Moving beyond regression techniques in cardiovascular risk prediction: applying machine learning to address analytic challenges. Eur Heart J. 38:1805–1814. doi: 10.1093/eurheartj/ehw302. https://www.baeldung.com/cs/svm-hard-margin-vs-soft-margin.

[9] Juliet A, Liam S, David A (2007). Hypertension in sub-saharan Africa: a systematic review. 50(6):10128. doi0.1161/HYPERTENSIONAHA.107.093336.

[10] Myers PD, Scirica BM, Stultz CM (2017). Machine learning improves risk stratification after acute coronary syndrome.Sci Rep. 7:12692. doi: 10.1038/s41598-017-12951-x.

[11] Poplin R, Varadarajan AV, Blumer K, Liu Y, McConnell MV, Corrado GS, Peng L, Webster (2018). Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning.Nat Biomed Eng. ; 2:158–164.doi: 10.1038/s41551-018-0195-0.

[12] Rapport RS. (1999). Hypertension. Silent killer. New Jersey Medicine: The Journal of the Medical Society of New Jersey, 96(3):41-43.

[13] Ross EG, Shah NH, Dalman RL, Nead KT, Cooke JP, Leeper NJ (2016). The use of machine learning for the identification of peripheral artery disease and future mortality risk.JVasc Surg. 64:1515–1522.e3. doi: 10.1016/j.jvs.2016.04.026.

[14] Schwartz CL, McManus RJ. (2015). What is the evidence base for diagnosing hypertension and for subsequent blood pressure treatment targets in the prevention of cardiovascular disease? BMC Med. 13:256.

[15] Stamler J (1991) Blood pressure and high blood pressure. Aspects of risk. Hypertension 1991; 18 (suppl 1) I-95 –I-107.

[16] Umoren I, Usua G. and Osang F. (2019). Analytic Medical Process for Ophthalmic Pathologies Using Fuzzy C-Mean Algorithm,Innov. Syst. Softw. Eng,

[17] Umoren, I., Udonyah K., and Isong E. (2019). "A Computational Intelligence Framework for Length of Stay Prediction in Emergency Healthcare Services Department," *2019 14th International Conference on Computer Science & Education (ICCSE)*, pp. 539-549, doi: 10.1109/ICCSE.2019.8845332.

[18] Umoren I. Etuk U. Ekong A. and Udonyah K. (2021). "Healthcare Logistics Optimization Framework for Efficient Supply Chain Management in Niger Delta Region of Nigeria" International Journal of Advanced Computer Science and Applications (IJACSA), 12(4) http://dx.doi.org/10.14569/IJACSA.2021.0120475

[19] W.H. O (2013) A Global Brief on Hypertension: Silent Killer, Global Public Health Crisis: World health day 2013, Tech. rep.

[20] Whelton PK, Carey RM, Aronow WS, Casey DE Jr, Collins KJ, Dennison Himmelfarb (2018). A guideline for the prevention, detection, evaluation, and management of high blood pressure in adults: a report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines. J Am CollCardiol. 71:127–248. https://doi.org/10.1016/j.jacc.2017.11.0

[21] Whelton PK, He J, Appel LJ, Cutler JA, Havas S, Kotchen TA, (2002). Primary prevention of hypertension: clinical and public health advisory from The National High Blood Pressure Education Program. JAMA. 288:1882–8.