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AUTISM SPECTRUM DISORDER PREDICTION USING ROBUST KALMAN FILTERING BASED NEURAL NETWORK

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ABSTRACT

Autism Spectrum Disorder (ASD) is a specific category of neurological disorder. A person affected by ASD faces lifelong effect in making communication and interaction with other common people. In individual's life, autism can be detected at any stage and it is also called behavioral disease. Symptoms of autism appear in the first three years of childhood and it continues its growth even if they reach adolescence and adulthood. Earlier prediction of ASD provides a way for recovery from ASD. Machine learning algorithms have been widely applied in various fields for better results. In this paper, Robust kalman filtering based neural network (RKFNN) is proposed to predict the ASD more accurately. In RKFNN has been modified to meet the prediction of ASD and it is integrated with neural network for better results. Results with better classification accuracy show the effectiveness of RKFNN towards the prediction of ASD.

Keywords: *Autism ,ASD, Classification, Kalman, Neural Network*

1. INTRODUCTION

Recently, the epidemic rate of autism spectrum disorder (ASD) has been surging exponentially across all ages and all sexes of the human race. Early diagnosis of this neurological condition allows the patient and the physician to preserve his or her mental and physical health[1]. As the use of machine learning models that can provide a probabilistic predictor for a patient's health and physiological data grows, it seems likely that early diagnosing of certain diseases using these probabilistic models could be possible. This aspect inspired us to raise interest in the diagnosis and study of ASD to help provide treatments to patients. ASD is problematic since there are too many different diseases that have seemingly identical effects to those of ASD[2]. Mental health providers must rapidly and reliably diagnose certain illnesses when administering drugs. Screening for Asperger's syndrome is a very complicated procedure as many different psychiatric conditions have similar effects to ASD.

ASD is considered a complication that has a relationship with the development of the human brain. Individuals who are all affected by ASD will not have the capability to make contact or communicate with other peoples. Good life experiences won't get happen in the whole lifespan of ASD affected persons. Though numerous factors may turn out to be causal as well as non-causative factors of this disease, researchers nevertheless plan to be vigilant in continuing to understand the causes of this disease[3],[4]. The indicator of ASD starts at the year of three and gets continued for the whole lifespan. It is not possible to fully cure this disease with any available experimental therapies. However, the consequences can be minimized for some period of time if the signs are identified at the early stage. Because the ancient genetic codes for autism have not been identified yet, scientists have to rely on the presumption that all human manifestations of autism are caused by this mutation. Environmental factors too act as a reason for the development of ASD in individuals[5],[6]. Optimization are used in various fields to enhance the expected results [7],[8]. Few risk factors that are related to ASD are lower birth weight, siblings with autism and so on. Instead, there are several social interaction issues with ASD affected persons, such as:

- Lack of contact with normal people
- Lack of social behaviour.

- Inappropriate laughter and jolliness.
- No sensation of pain was observed.
- Difficulty in making eye contact.
- No proper reaction to the tone of speech.
- Not able to communicate the action of movements.
- No contact with other people.
- Inappropriate attachment of artifacts.
- Willing to live lonely.
- Using echo terms and phrases.

People having the condition of ASD show difficulties with preferences and habits, which can also become repetitive. Some of the precise examples of ASD peoples are:

- Repetition of words or phrases to get the expected of a specific term.
- The individual will feel some unpleasant emotions when a routine is changing.
- Even showing a little of an interest in a minor issue.
- Having low-level sensitivity than an ordinary person in noise, light, etc., if it does not work.

Early diagnosis and care is the most significant steps to minimize ASD symptoms and to increase the quality of life. However, there is currently no medical examination to find out whether a person is autistic. ASD signs may typically be identified by observation.

Machine Learning algorithms are widely applied in healthcare for the prediction of disease and it helps in minimizing medical costs. Currently available machine learning algorithms for the prediction of ASD are facing many issues in terms of classification accuracy. Misclassification can lead to a severe effect on the patients life.

This paper attempts to propose a machine learning-based algorithm to effectively classify ASD, namely Robust Kalman Filtering based Neural Network. It ensembles a modified version of Kalman filtering with a neural network for enhanced classification accuracy.

2. LITERATURE REVIEW

Naïve Bayes, Support Vector Machine, Logistic Regression and Convolutional Neural Network (CNN) are applied to detect Autism Spectrum Disorder [9]. These methods are attempted to detect ASD among adults, adolescents and children. It showed the result that CNN provides result in handling missing values. Linear Support Vector Machine [10] is applied to predict Chronic Bipolar Disorder in an earlier intervention. This is validated using Cambridge neuropsychological test automated battery. The trained dataset is applied to evaluate the efficiency of the algorithm. Results make a clear indication that impairments of cognition were present in earlier stages and it continues till the last stages. Machine learning with big data [11] is applied to build a better prediction towards the discovery of psychiatry. It offers a better opportunity in the field of mental health research. It builds a new model for identifying the diseases with semi-structured medical data and multi-domain data, where it assists in discovering and personalizing the therapeutics. Random Forest classifier [12] is applied to predict the depression, anxiety and stress among employees across different countries and it was collected using a questionnaire. To find the exact algorithm to predict the psychological problems, the Random Forest classifier is compared with four different classifiers. Results indicate that the compared classifier has poor performance towards classifying and predicting the psychological problems. Machine Learning-based Approach [13] is proposed to differentiate panic disorder among psychiatry patients. The artificial neural network, Random Forest, Support vector machine, logistic regression, and gradient boosting machine algorithms are used for making the differentiation. Results made an indication that logistic regression has better performance in differentiating the panic disorder among psychiatry patients.

Predictive performance [14] is proposed to predict the symptoms of depression among different patients. A comparison was made with a statistical approach namely logistic-regression. Results show that predictive-performance has better classification accuracy than logistic regression. Complex Network Measure [15] proposed to predict ASD with the aid of a machine learning framework. It analyzes the network topology of brain functions and it was found that some specific information regarding ASD is not present in bivariate connectivity. A comparison was made with a support vector machine for verifying the efficiency. Computational Psychiatry [16] attempted to utilize multi-level analysis to detect mental dysfunction. Cost benefits and adaptivity of the environment are mainly considered for detecting mental dysfunction. Artificial computational devices are used to empower the navigation. Neuro-Computational framework [17] is established to illustrate cognition might go wrong towards Obsessive-Compulsive Disorder (OCD). Abnormal neural processes ensemble with neuroimaging to find OCD. Result provides information that OCD can be characterized by the presence of disruptions. Genome-wide logistic regression [18] was proposed to find the important variants that are related to duloxetine response. Extraction was done to find the trusted predictors utilizing the regression model. Additionally, the classification-regression tree has been ensembled with the SVM algorithm to build models.

Machine learning-based neuroimaging [19] proposed to detect health issues that are linked with depression and bipolar disorder. It makes a direct translation of findings to the practice of healthcare and sophisticated classifications are applied to clinical and subtype of diagnosis. The readmission Model [20] is proposed to predict the readmission of mental disorder patients to the hospital. It makes a continuous analysis of patient admission to hospital utilizing area-under receiver-operating-characteristic method and performance comparison has been made against the boosted tree to generalize the linear model.

To detect ASD at an early stage SVM algorithm [21] is applied. Different feature selection methodology is used along with Z-score transformed dataset. It is compared with the Adaboost algorithm for the performance analysis and it found SVM has better performance than the Adaboost algorithm. To overcome the issues faced in associative classification towards detection of ASD, Active Pruning Rules [22] is proposed. It attempts to enhance the classification accuracy and minimizing the rule followed in redundancy rule. Rules followed in the classification are discarded in the training data.

3. ROBUST KALMAN FILTERING BASED NEURAL NETWORK

Kalman Filtering has started its footprint in multiple research areas that include tracking, estimation and disease prediction. Kalman filtering is most commonly utilized in the estimation of the linear dynamic system state via the results gathered previously. Consider $y \in S^m$ as discrete linear system state and $a \in S^p$ as the measurement. Eq.(1) and Eq. (2) will satisfy the current state and measurement at time l.

$$y_l = C_l y_{l-1} + D_l v_l + x_l \tag{1}$$

$$a_l = I_l y_l + w_l \tag{2}$$

where y_l represents the current state, $v_l \in S^n$ represents the controlling input, a_l indicates the term used for measuring, C_l is a $m \times m$ matrix that enables the relationship with $(l-1)$ and l state of time, D_l is a $m \times n$ matrix that enables the relationship with controlling input and the current state, I_l is a matrix that enables the relationship between the current state and measurement. x_l and w_l presents the process and measurement error which is considered to be a variable that is randomly selected between 0 and covariant matrices E_l and F_l, respectively.

In estimating the state, Kalman filtering hold two different phases namely (i) prediction phase and (ii) updation phase. In the prediction phase, Kalman filtering utilizes the information gathered from the preceding state to make an estimation about priori (pr) current state, where its estimation is updated by making use of the information gathered and it results in the generation of posteriori (po) current state in updation phase. Eq.(3) to Eq. (7) defines the prediction phase and updation phase.

Prediction Phase:

$$y_l^- = C_l y_{l-1} + D_l v_l \tag{3}$$

$$U_l^- = C_l U_{l-1} C_l^Y + R_l \tag{4}$$

Updation Phase:

$$L_l = U_l^- I_l^Y (I_l U_l^- I_l^Y + F_l) \tag{5}$$

$$y_l = y_l^- + L_l (a_l - I_l y_l^-) \tag{6}$$

$$U_l = (J - L_l I_l) U_l^- \tag{7}$$

where $y_l^- \epsilon F^m$ is the estimation of pr state, U_l^- represents pr's $m \times m$ matrix, U_l represents po's $m \times m$ matrix, Kalman gain is indicated as L_l and it is represented as $m \times q$ matrix.

While using trained Neural Network (NN) for classifying an object among one of the N classes, then NN input layer holds M neurons corresponding to the features $fs_1, fs_2, fs_3, \dots, fs_M$ and the output layer N neurons that correspond to the expected output $s_1, s_2, s_3, \dots, s_N$, where

$$a_j = \begin{cases} 1 & \text{if the expected object falls in class } d_j \\ 0 & \text{otherwise}, \quad j = 1,2,3 \dots, N \end{cases} \tag{8}$$

Assume $a_1, a_1, a_3, \dots, a_N$ be the output of NN that is predicted, the values of a_j for all $j = 1,2,3, \dots, N$ confirms the correct classification of objects. The proposed Robust Kalman Filtering based NN $(RKFNN)$ post-process the NN classifier to enhance the performance of classification. $RKFNN$ utilizes the NN's predicted output as input for estimating the class label.

RKFNN consists of two significant phases namely training and testing. Different Stages involved in training are:

- Training of NN
- Predicting NN output regarding the object present in NN
- Classifying the objects present in training by using NN output
- Computing the NN's accuracy of classification
- Constructing the linear model
- Estimating the RKFNN parameters using Kalman filter
- Predicting the RKFNN output
- Computing the RKFNN accuracy of classification

Different Stages involved in testing are:

- Predicting the RKFNN output
- Classification of objects utilizing RKFNN

RKF is developed to make an adjustment with the NN's predicted output, i.e., the accuracy of classification is enhanced by making use of object features linear combination. Hence, independent variables of RKF hold features $fs_1, fs_2, fs_3, \dots, fs_M$ and NN's predicted output $a_1, a_2, a_3, \dots, a_N$ where dependent variables are expected outputs $eo_1, eo_2, eo_3, \dots, eo_N$.

Additionally, an assumption is made that the proposed model has error 0 and covariant matrix F and it is mathematically expressed as Eq. (9)

$$eo = Cz + Dfs + w \tag{9}$$

Where $eo = [eo_1, eo_2, eo_3, \dots, eo_N]^V$, $z = [z_1, z_2, z_3, \dots, z_N]^V$, $z = [z_1, z_2, z_3, \dots, z_N]^V$, $fs = [fs_1, fs_2, fs_3, \dots, fs_N]^V$, C represents $N \times N$ diagonal matrix formulated in Eq. (10) and D represents a $N \times M$ matrix formulated in Eq. (11), w indicates the term error. C and D are the matrices of the linear model having unknown parameters.

$$C = diag[p_{11} \quad p_{22} \quad p_{33} \quad \cdots \quad p_{NN}] \tag{10}$$

$$D = \begin{bmatrix} f_{11} & f_{12} & f_{13} & \cdots & f_{1M} \\ f_{21} & f_{22} & f_{23} & \cdots & f_{2M} \\ f_{31} & f_{32} & f_{33} & \cdots & f_{3M} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{N1} & f_{N2} & f_{N3} & \cdots & f_{NM} \end{bmatrix} \tag{11}$$

To perform the estimation of parameters present in the linear model (Eq. (9)) by making use of Kalman filter, the equation for processing and measuring is necessary to be defined. Linear model parameters of Eq. (9) are the static values where the state won't change at different times. The systems dynamicity at time l is mathematically expressed as Eq. (12).

$$y_l = y_{l-1} + x_l \tag{12}$$

where x_l is the random variable error having a mean value as 0 and covariant matrix R.

The linear model present in Eq. (9) is utilized as a measuring tool with a minor change as expressed in Eq. (13)

$$a_l = I_l y_l + w_l \tag{13}$$

where $I = \partial a / \partial y$ represents a jacobian matrix of a and its all elements have first-order partial derivation elements of a.

Based on Eq. (12) that is used for processing, Eq. (13) that is used for measuring, Eq. (3) to Eq. (7) used in prediction and updation

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phases present in Kalman filtering are executed using Eq. (14) to Eq. (18).

Prediction Phase:

$$y_l^- = y_{l-1} \quad (14)$$

$$U_l^- = U_{l-1} + E \quad (15)$$

Updation Phase:

$$L_l = U_l^- I_l^Y (I_l U_l^- I_l^Y + F)^{-1} \quad (16)$$

$$y_k = y_k^- + L_l (a_l - I_l y_l^-) \quad (17)$$

$$U_l = (J - L_l I_l) U_l^- \quad (18)$$

Before the action performs in Kalman filtering, the values of E, F, y_0 and U_0 is necessary to be assigned initially. Hence there exists no information regarding the values of E and F, RKFNN assumes E as scalar matrix and F as another scalar matrix. E and F are considered to be in the form $E = eJ$ and $F = fJ$, where e and f are real numbers having positive values and it is selected as the term that increases the accuracy of classification. Further, y_0 and U_0 are selected as the beginning values of y and U respectively. The iteration of the proposed work is performed through the whole training data till the condition for the convergence is met.

4. RESULTS AND DISCUSSION

4.1 About Dataset

In this paper, three different datasets [2],[23],[24] are used for analyzing the performance of the proposed classifier towards predicting ASD. Details of the datasets are provided in Table 1 and the details of attributes are provided in Table 2.

Table 1: ASD Dataset

Sl .N o	Name of Dataset	Attributes	Instances Count	Attribute Type
1	ASD Screening Dataset for Adults (Thabtah, 2017a)	21	704	(a) Categorical (b) Continuous (c) Binary
2	ASD Screening Dataset for Children (Thabtah, 2017c)	21	292	(a) Categorical (b) Continuous (c) Binary
3	ASD Screening Dataset for Adolescents (Thabtah, 2017b)	21	104	(a) Categorical (b) Continuous (c) Binary

Table 2 describes the attributes present in ASD dataset [2],[23],[24].

Table 2: Attributes of ASD Dataset

Attribute Id	Description of Attribute
1	Age of the patient
2	Gender of the patient
3	Ethnicity of the patient
4	Born with jaundice
5	Family member with Pervasive Development Disorders
6	Who is completing the test
7	Country of residence
8	Whether the screening App used by the user earlier or not?
9	Type of Screening Method
10-19	Based on the screening method answers of 10 questions
20	Score of Screening

4.2 Performance Metrics

Four different variables that are used in the calculation of performance metrics are:

- True Positive (TP): Exact detection of the presence of ASD
- False Positive (FP): Incorrect detection of the presence of ASD
- True Negative (TN): Exact detection of the absence of ASD
- False Negative (FN): Incorrect detection of the absence of ASD

Above mentioned variables are used in the calculation of performance metrics, which are:

$$Sensitivity = \frac{TP}{TP + FN} \quad (19)$$

$$Specificity = \frac{TN}{TN + FP} \quad (20)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{21}$$

$$Precision = \frac{TP}{TP + FP} \tag{22}$$

$$Recall = \frac{TP}{TP + FN} \tag{23}$$

$$F - Measure = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{24}$$

4.3 Analysis of Adult Dataset for ASD

In Figure 1, the variables TP, TN, FP and FN are plotted on the x-axis and the y-axis is plotted with the count of records. It is very clear to understand that RKFNN has better performance against previous algorithms namely SVM [21] and Active Pruning Rules [22]. The prediction phase and the updation phase in RKFNN assist better results in predicting ASD.

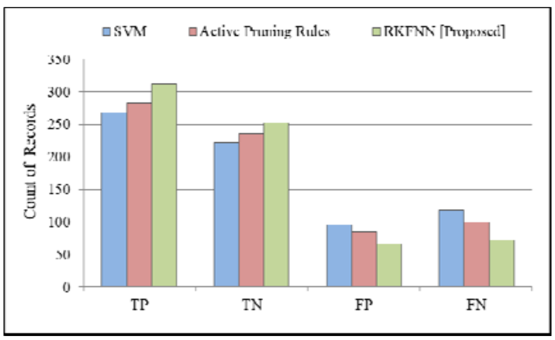

Figure 1: Adult Dataset vs TP, TN, FP, FN

In Figure 2, the performance metrics Sensitivity, Specificity and Accuracy are plotted on the x-axis and the percentage of results is plotted on the y-axis. From the figure, it has been observed that RKFNN has outperformed the other two algorithms namely SVM [21] and Active Pruning Rules [22]. The linear model present in RKFNN assists the classifier to perform better classification. SVM [21] and Active Pruning Rules [22] would have ignored the significant features and this result in poor classification.

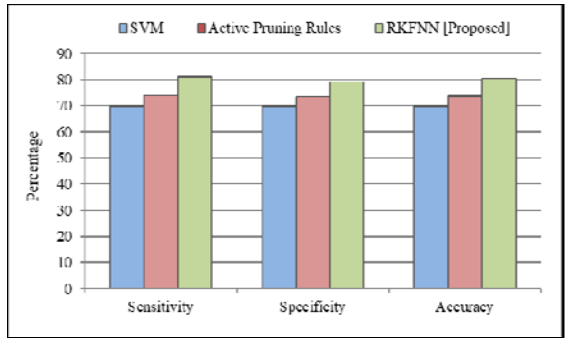

Figure 2: Adult Dataset vs Sensitivity, Specificity, Accuracy

In Figure 3, the performance metrics Precision, Recall and F-Measure are plotted on the x-axis and the percentage of results is plotted on the y-axis. From the figure, it is evident that RKFNN has better performance in terms of precision, recall and f-measure than SVM [21] and Active Pruning Rules [22]. RKFNN applies predicted output as input for estimating the class label and this assists to achieve better results.

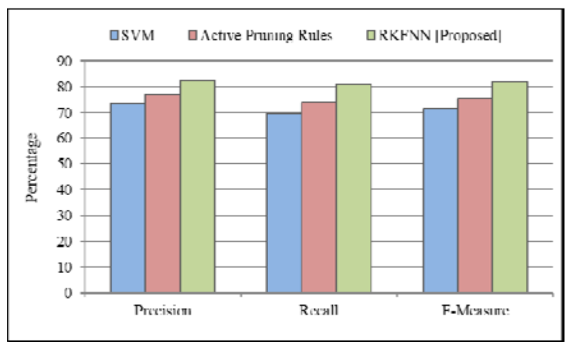

Figure 3: Adult Dataset vs Precision, Recall, F-Measure

4.4 Analysis of Children Dataset for ASD

In Figure 4, the variables TP, TN, FP and FN are plotted on the x-axis and the y-axis is plotted with the count of records. It is very clear to understand that RKFNN has better performance against previous algorithms namely SVM [21] and Active Pruning Rules [22]. The prediction phase and the updation phase in RKFNN assist better results in predicting ASD. While making a notice on FP, it was found that SVM [21] and Active Pruning Rules [22] has the minimum level difference.

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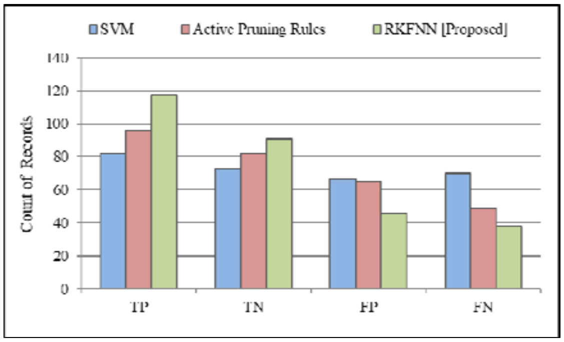

Figure 4: Children Dataset vs TP, TN, FP, FN

In Figure 5, the performance metrics Sensitivity, Specificity and Accuracy are plotted on the x-axis and the percentage of results is plotted on the y-axis. From the figure, it has been observed that RKFNN has outperformed the other two algorithms namely SVM [21] and Active Pruning Rules [22]. The linear model present in RKFNN assists the classifier to perform better classification. SVM [21] and Active Pruning Rules [22] would have ignored the significant features and this result in poor classification.

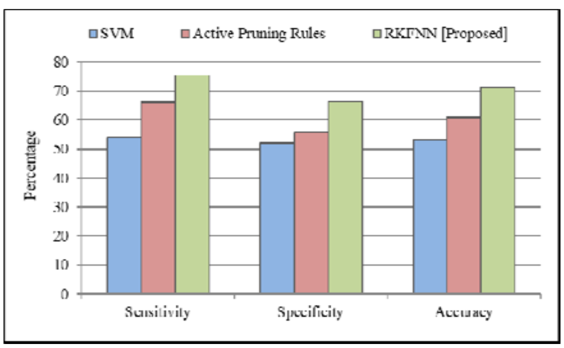

Figure 5: Children Dataset vs Sensitivity, Specificity, Accuracy

In Figure 6, the performance metrics Precision, Recall and F-Measure are plotted on the x-axis and the percentage of results is plotted on the y-axis. From the figure, it is evident that RKFNN has better performance in terms of precision, recall and f-measure than SVM [21] and Active Pruning Rules [22]. RKFNN applies predicted output as input for estimating the class label and this assists to achieve better results.

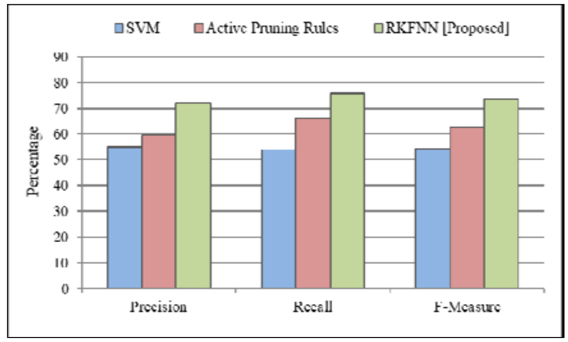

Figure 6: Children Dataset vs Precision, Recall, F-Measure

4.5 Analysis of Adolescent Dataset for ASD

In Figure 7, the variables TP, TN, FP and FN are plotted on the x-axis and the y-axis is plotted with the count of records. It is very clear to understand that RKFNN has better performance against previous algorithms namely SVM [21] and Active Pruning Rules [22] in terms of TP, FP and FN. But, while noticing TN it is found that Active Pruning Rules [22] has a minor level better performance than RKFNN. The prediction phase and the updation phase in RKFNN assist better results in predicting ASD.

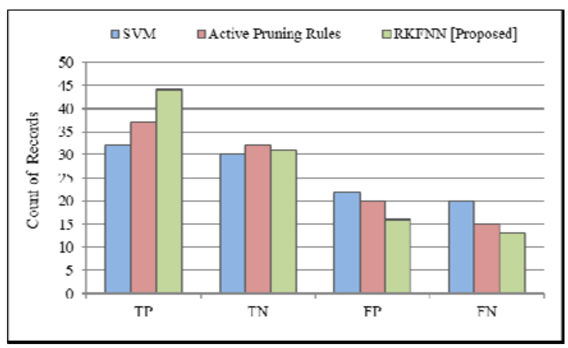

Figure 7: Adolescent Dataset vs TP, TN, FP, FN

In Figure 8, the performance metrics Sensitivity, Specificity and Accuracy are plotted on the x-axis and the percentage of results is plotted on the y-axis. From the figure, it has been observed that RKFNN has outperformed the other two algorithms namely SVM [21] and Active Pruning Rules [22]. The linear model present in RKFNN assists the classifier to perform better classification. SVM [21] and Active Pruning Rules [22] would have ignored the significant features and this result in poor classification.

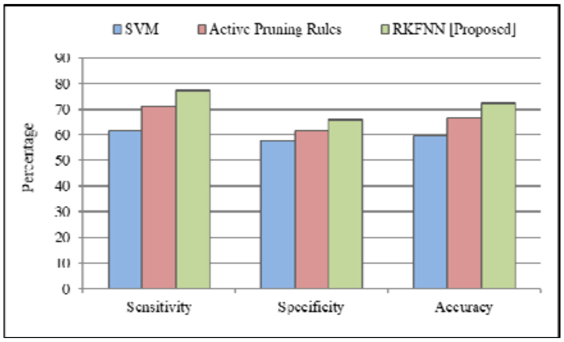

Figure 8: Adolescent Dataset vs Sensitivity, Specificity, Accuracy

In Figure 9, the performance metrics Precision, Recall and F-Measure are plotted on the x-axis and the percentage of results is plotted on the y-axis. From the figure, it is evident that RKFNN has better performance in terms of precision, recall and f-measure than SVM [21] and Active Pruning Rules [22]. RKFNN applies predicted output as input for estimating the class label and this assists to achieve better results.

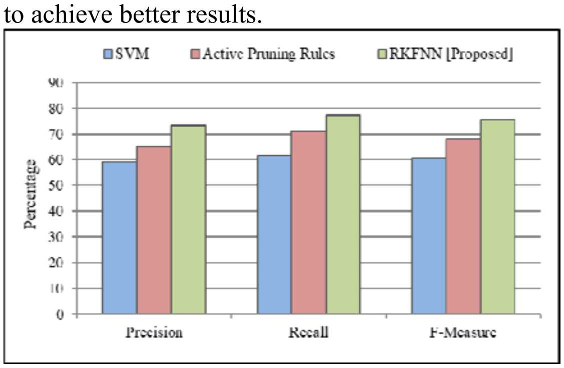

Figure 9: Adolescent Dataset vs Precision, Recall, F-Measure

4.6 Classification Accuracy Comparison

Table 3 provides the classification achieved by proposed classifier RFFNN against existing classifier SVM and Active Pruning Rules. Results make an indication that proposed classifier has better performance than existing classifiers.

Table 3: Classification Accuracy

Algorithms	Adolescent Dataset	Children Dataset	Adult Dataset
SVM	59.6154 %	53.0822 %	69.7443 %
Active Pruning Rules	66.3462 %	60.9589 %	73.7216 %
RKFNN	72.1154 %	71.2329 %	80.2557 %

5. CONCLUSION

In this paper, Robust Kalman Filtering based Neural Network (RKFNN) has been proposed to classify ASD affected persons more effectively. The modified version of Kalman filtering is ensembled with a neural network for increased classification accuracy. The prediction phase and updation phase assist the classifier to achieve better accuracy. Three benchmark dataset has been chosen to evaluate the performance of RKFNN against previously available algorithms for the prediction of ASD. Benchmark metrics are used to measure the performance of RKFNN. Results make an indication that RKFNN has better performance in predicting ASD than other algorithms. In order to get better accuracy than the obtained result, the same work can be extended with optimization based classification.

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