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Enhanced Prediction of Autism Spectrum Disorder Using Kalman Filtering Based Support Vector Machine

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ABSTRACT

Autism Spectrum Disorder (ASD) is a category of complex neuro-developmental problems. ASD involves poor speech, limited desires, and repeated behavior. Early diagnosis of autism provides an opportunity an effective treatment. The challenges in correctly classifying and predicting ASD result in discouragement in seeking successful interventions. Machine learning techniques are being applied in medical fields for the prediction of diseases which would save precious time and cost. All machine learning algorithms won't provide its better efficiency in predicting all diseases and it is limited. An algorithm that gives better performance in predicting a disease won't give the same performance in predicting other diseases. This paper proposes an algorithm namely Kalman Filtering Based Support Vector Machine (KFSVM) to effectively predict the ASD. Optimum hyperplane in KFSVM assist better classification. To analyze the effective performance of KFSVM against previous algorithms it has been tested with three different ASD screening datasets available for adults, children and adolescents. Results are measured using benchmark data mining metrics and it has been found that KFSVM has better performance in classifying and predicting ASD in all considered datasets.

Keywords
ASD, Autism, Classification, Kalman, SVM

Introduction

ASD constitutes a conglomeration of various psychiatric syndromes. It is not that easy to predict and regulate social contact among multiple disorders. The recent appreciation of ASD by physicians and caregivers is considered to have played a leading role in the early diagnosis of autism and early active intervention[1]. Latest studies have investigated the outcomes of diagnosis or therapeutic approaches on young children with ASD. However, facts of improvements owing to the inconsistent consistency of classifications of ASD using standardized tests where classifications are reduced in number and variety [2][1][3]. A few experiments looked at the stability of the diagnostic approach for autism. The exact time for diagnosing children with ASD falls in the first two years of their lives[4].

Due to the intensity, severity and correlation of ASD symptoms with other diseases, it is important to use suitable instruments and scales to reliably and efficiently diagnose ASD. Methods such as interviews and observations are standard tools used by clinicians evaluating ASD[5][6]. Although the signs of mental illness are so complex, it is important to ascertain if the patient is genuinely suffering from an illness, not a panic attack or a normal psychiatric condition. Individuals with ASD, where the condition of intellectual disability is present, may be diagnosed with ASD if they have at least three characteristics of social contact and at least two characteristics of limited or repeated behaviors; and as well as a recent addition of heightened and/or uncommon involvement in sensory dimensions of the setting[7][8]. Another recent diagnosis of social communication disorder (SCD) has been created in children that are less than 3 years old. Before this, they match the definition of ASD. The reason they are diagnosed with SCD is that they suppress repetitive habits, but also suffer from verbal and nonverbal speech deficiencies that adversely influence their social interactions[9][10].

Data mining techniques provide an automatic, efficient and accurate model of classification for the ASD problem as they use a mixture of mathematics and computer science algorithms[11][12]. Since the beginning of the field of data mining, multiple algorithms have been developed to solve various problems. In the field of data mining, the question

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is raised concerning ASD identification, where the challenge is to decide which cases fall into the ASD label, and which do not[13][14].

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 patient's life

Literature Review

Feature Representation [15] is proposed with deep neural network to enhance the classification of ASD. Initially, brain network is constructed for individual subject and perform extraction of connectivity features. Secondly, ranks are allocated for connectivity features with the utilization of F-score. Lastly, top ranked features are used in the classification process. Outliers based Machine Learning Approach [16] aimed to increase the classifications generalizability. It adopts auto-encoder for identifying the outliers and confounding index to enrich the find the samples that leads the classification to mislead. This avoids the scarcity of data when it is ensembled with heterogeneous sample data. Fisher Discriminant Analysis [17] aimed to fix the classification model to effectively classify ASD cases. Metabolites are applied in the prediction of ASD where it does not have that much performance towards distinguishing ASD and predicting ASD at the earliest. Fuzzy Cognitive Map Ensemble Learning [18] inherits the important aspects of boosting and bagging to predict ASD. Bagging is used to classification and boosting is used enhancing the classification accuracy. Dataset has been trained with non-linear Hebbian learning, where neural network used for learning.

SVM-recursive feature elimination method [19] is proposed identify the optimum features present in functional connectivity that lead to increased classification accuracy. Feature selection is processed and fed as input to Gaussian kernel based SVM algorithm. Multivariate Classification [20] has studied the low frequency imaging affect on brain functional connectivity in ASD individuals. Bands of specific frequency utilized in discriminating the controls and relationship that have severe symptoms. ASD identification method [21] proposed with the base of deep feature representation that utilize multi-atlas. It computes the multi-functional connectivity at various atlases of brain gathered from FMRI data. Feature selection is performed by using stacked denoising autoencoder. Lastly, multilayer perceptron is performed for identifying the ASD. Recurrent Attention Model [22] proposed as a deep learning technique for classifying ASD. Policy Gradient algorithm plays a major role in this model to experience the Gaussian sampling. Information regarding the error faced in time difference and training are rectified are to increase the accuracy of classification.

Deep Generative State-Space Modeling [23] proposed as a temporal model to understand the mechanism that act as a root cause for disorders. Deep learning methodology is utilized as a state space model that overcomes the issues of overfitting and acts better than normal deep-learning classification algorithms. Mental Disorder Screening System [24] proposed as a single-lead ECG system which combines the features of mental oriented tasks. It mainly focused on the varying heart rates. SVM is used classify the somatoform disorders with 24 psychiatric patients. Result of the non-linear classification model makes an indication that it has achieved low accuracy than the existing models. Computational Psychiatry [25] 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 [26] 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. Optimization [32],[33] is a technique to enhance the results in different research streams and it is used in classification also.

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Kalman Filtering Based Support Vector Machine

Consider a set of training samples that are identical and independently distributed (id-ip-d), where classification's input and output are indicates as $a_j \epsilon S^M$ and $b_j \epsilon\{-1,1\}$. SVM functions are created with a utilization of hyperplane that differentiate dataset to two different classes. According to the methodology of Structural Risk Minimization (SRM) states that it is optimum to have only one hyperplane which have more distance between data points of individual classes. The data points that falls close to the optimum hyperplane are denoted as Support-Vectors (SV). Eq.(1) defines the mathematical expression of the hyperplane and Eq.(2) is applied to find the maximum margin by subtracting the value $(0.5 \times \|p\|^2)$ from Eq.(1).

$$p.a + f = 0 \tag{1}$$

$$(p.a + f) - (0.5 \times \|p\|^2) = 0 \tag{2}$$

Optimum hyperplane that is used separation is established by subtracting Eq.(2) from Eq.(3) and it will result in exact separation of training data.

$$b_j\left(a_j.p + f\right) > 1, \qquad for\ all\ \ j \tag{3}$$

The method of optimum hyperplane that is used for separating is established for cases that are not separable and it introduces the cost for offending the constraints that are used for separation. It is achieved by introducing the slack variables μ that have value greater than 1 in Eq.(3) and it is expressed in Eq.(4).

$$b_j\left(a_j.p + f\right) > 1 - \mu, \qquad for\ all\ \ j \tag{4}$$

If there occurs any transgression, then the equivalent μ should have maximum value. Hence, $\sum_j \mu_j$ ranks first in the classification transgression. Hence, the logical way to fix the additional cost for transgression is to minimize the objective specified in Eq.(2).

$$\min\left((0.5 \times \|p\|^2) + (CP \times \left(\sum_i \mu_i\right)\right) \tag{5}$$

where CP denotes the parameter that is chosen. Maximum CP denotes the increased transgression leading to misclassification. Difference between Eq.(5) and Eq.(4) provides the established optimum hyperplane used for separation. This act as a quadratic programming problem (QPP) that gets resolved with the aid of Lagrangian multipliers.

Once after processing the necessary calculations, QPP is resolved by identifying the lagrangian multipliers z_i that increases the objective function using Eq.(6)

$$P(z) = \sum_{j=1}^{m} z_j - 0.5\left(\sum_{j,k=1}^{m} z_j z_k\, b_j b_k \left(a_j^U b_k\right)\right) \tag{6}$$

Eq.(6) is subject to $0 < z_j < CP, j = 1,2,3, \dots, (m-1), m$ and Eq. (7)

$$\sum\nolimits_{j=1}^{m} z_i b_i = 0 \tag{7}$$

New objective function is dependent on z_i i.e., multipliers of lagrangian multipliers. It is considered as twin problems which are (i) while knowing p, it is possible to find all z_i (ii) while knowing z_i, it is possible to find all p. Most values of z_i are '0' where p becomes linearly minimum of all data points. a_j with a value that is not '0' z_i are termed as support vectors. The boundary of decision is established only on the dependent of SV. Consider $u_k(k = 1,2,3,\dots,(t-1),t$ represent the indices of t support vectors. It can be mathematically expressed as

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$$p = \sum_{k=1}^{t} z_{u_k} b_{u_k} a_{u_k} \quad (8)$$

Till now, this research work has used linear separation decision model. If decision model is not linear means, data will be plotted via input space to maximum dimension space by a non-linear function of transformation. In this current feature space, optimum hyperplane is constructed.

Introduction of Kernel function in SVM will never make ϕ to explicitly disclose and it is expressed in Eq.(9).

$$KF(a_j, a_k) = \{\phi(a_j), \phi(a_k)\} \quad (9)$$

Optimization problem present in Eq.(6) can be reframed based on kernel function.

$$P(z) = \sum_{j=1}^{m} z_j - 0.5\left(\sum_{j,k=1}^{m} z_j z_k\, b_j b_k KF(a_j a_k)\right) \quad (10)$$

Eq.(10) is subject to $CP > z_i > 0$ and $\sum_{j=1}^{m} z_i b_i = 0$.

After calculating z_i variables, hyperplane equation is mathematically expressed as

$$d(x) = \sum_{j=1}^{l} b_j z_j KF(a, a_j) + f \quad (11)$$

To perform classification against test data Eq.(12) is expressed where newly received data from dataset is classified as $class - 1$ if $j > 0$ and $class - 2$ if $j < 0$.

$$j_g(a) = sign\,[d(x)] = sign\left[\sum_{j=1}^{l} b_j z_j KF(a, a_j) + f\right] \quad (12)$$

Linear based system and processing model in the duration kf and $kf + 1$ is defined as in Eq. (13):

$$a_{kf+1} = STMa_{kf} + GCr_{kf} + s_{kf} \quad (13)$$

where a_{kf} and a_{kf+1} represents the state of the system during the period kf and $kf + 1$. STM indicates matrix of system transition. GC denotes the gain control r_{kf}. s_{kf} indicates the noise of Gaussian process with the mean zero. Initially, a_0 is considered to follow $a_0 \sim M(a_0, Q_0)$ which is a Gaussian distribution model. The main intention is to make estimation about the state by the processing model with its observations. During the time $kf + 1$, the observation is mathematically shown in Eq.(14).

$$c_{kf+1} = Da_{kf+1} + e_{kf+1} \quad (14)$$

In Eq.(13), D indicates the matrix used for observation and e_{kf+1} represents the noise of Gaussian process with the mean zero $e_{kf+1} \sim F(0, G)$.
If the gathering of knowledge on a_{kf} at the time kf is

$$a_{kf} \sim F(a_{kf}, Q_k) \quad (15)$$

Also, a_{kf+1} at the time $kf + 1$ will follow Eq. (16)

$$a_{kf+1} \sim F(a_{kf+1}, Q_{k+1}) \quad (16)$$

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where a_{kf+1} and Q_{kf+1} will be calculated using the $k$alman $f$ilter formula.

Prediction using the model of processing is expressed in Eq.(17)

$$a_{kf+1} = STMa_{kf} + GCr_{kf} \tag{17}$$

$$Q_{kf+1} = \left(STM \times Q_{kf} \times STM^{U}\right) + R \tag{18}$$

Applying the observation in update

$$\widetilde{a_{kf+1}} = a_{kf+1} + KF\left(c_{kf+1} - Da_{kf+1}\right) \tag{19}$$

Results And Discussion

About Dataset

In this paper, three different datasets [27][28][29] 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

S.No	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 (Thabtah, 2017a, 2017c, 2017b).

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

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10-19	Based on the screening method answers of 10 questions
20	Score of Screening

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:

$$Sensitivity = \frac{TP}{TP + FN} \tag{20}$$

$$Specificity = \frac{TN}{TN + FP} \tag{21}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{22}$$

$$Precision = \frac{TP}{TP + FP} \tag{23}$$

$$Recall = \frac{TP}{TP + FN} \tag{24}$$

$$F - Measure = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{25}$$

Analysis of Adult Dataset for ASD

In Figure 1, the variables TP, TN, FP and FN are marked on the x-axis and the y-axis is marked with the count of records. It is very clear to understand that KFSVM has better performance against previous algorithms namely SVM [30] and Active Pruning Rules [31]. The prediction phase and the updation phase in KFSVM assist better results in predicting ASD.

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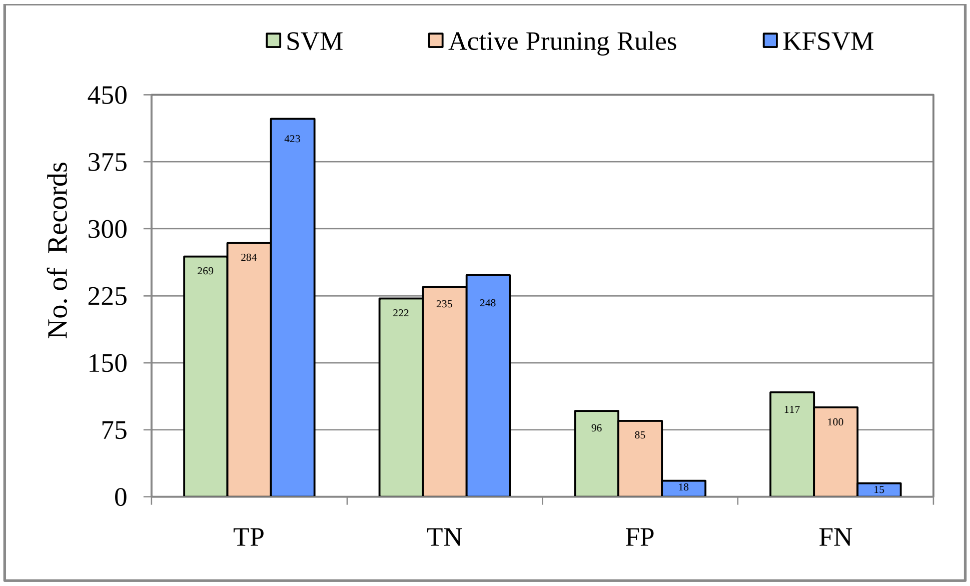

Figure 1. Adult Dataset vs TP, TN, FP, FN

In Figure 2, the performance metrics Sensitivity, Specificity and Accuracy are marked on the x-axis and the percentage of results is marked on the y-axis. From the figure, it has been observed that KFSVM has outperformed the other two algorithms namely SVM [30] and Active Pruning Rules [31]. The linear model present in KFSVM assists the classifier to perform better classification. SVM [30] and Active Pruning Rules [31] would have ignored the significant features and this result in poor classification.

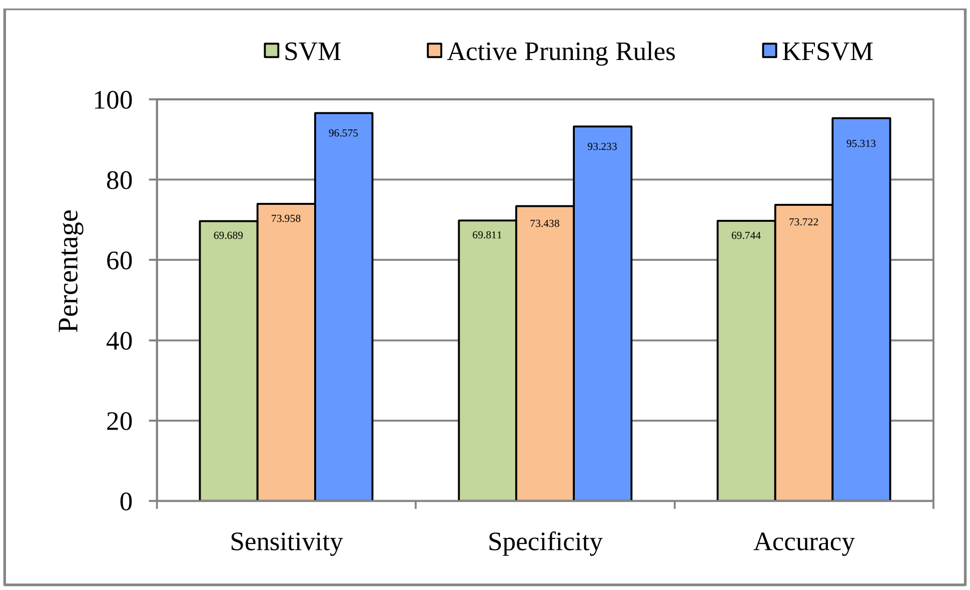

Figure 2. Adult Dataset vs Sensitivity, Specificity, Accuracy

In Figure 3, the performance metrics Precision, Recall and F-Measure are marked on the x-axis and the percentage of results is marked on the y-axis. From the figure, it is evident that KFSVM has better performance in terms of precision, recall and f-measure than SVM [30] and Active Pruning Rules [31]. KFSVM applies predicted output as input for estimating the class label and this assists to achieve better results.

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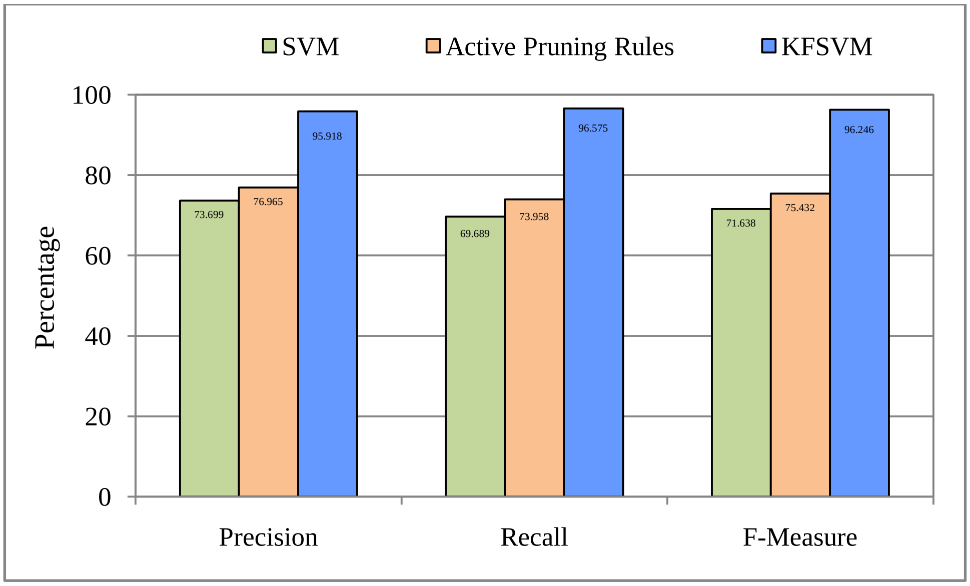

Figure 3. Adult Dataset vs Precision, Recall, F-Measure

Analysis of Children Dataset for ASD

In Figure 4, the variables TP, TN, FP and FN are marked on the x-axis and the y-axis is marked with the count of records. It is very clear to understand that KFSVM has better performance against previous algorithms namely SVM [30] and Active Pruning Rules [31]. The prediction phase and the updation phase in KFSVM assist better results in predicting ASD. While making a notice on FP, it was found that SVM [30] and Active Pruning Rules [31] has the minimum level difference.

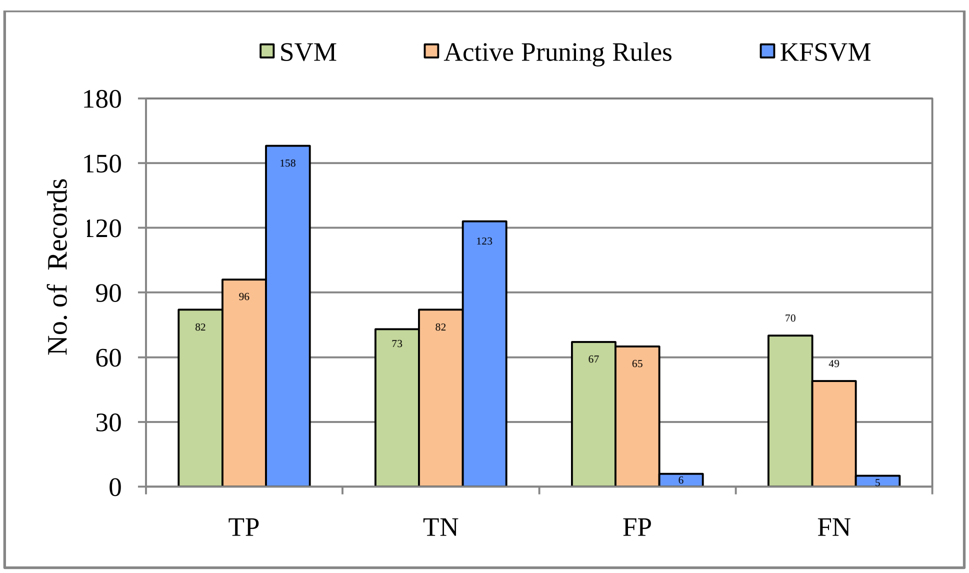

Figure 4. Children Dataset vs TP, TN, FP, FN

In Figure 5, the performance metrics Sensitivity, Specificity and Accuracy are marked on the x-axis and the percentage of results is marked on the y-axis. From the figure, it has been observed that KFSVM has outperformed

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the other two algorithms namely SVM [30] and Active Pruning Rules [31]. The linear model present in KFSVM assists the classifier to perform better classification. SVM [30] and Active Pruning Rules [31] would have ignored the significant features and this result in poor classification.

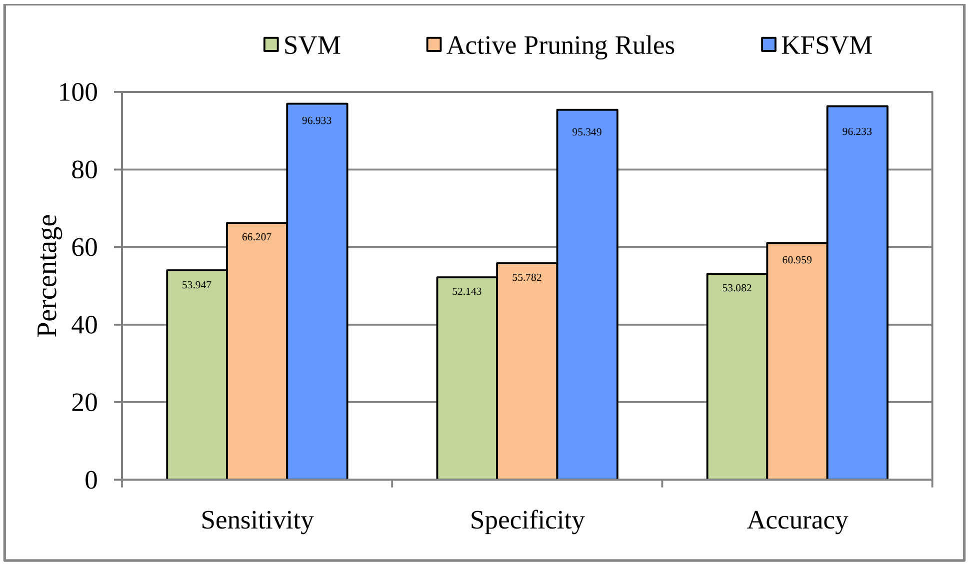

Figure 5. Children Dataset vs Sensitivity, Specificity, Accuracy

In Figure 6, the performance metrics Precision, Recall and F-Measure are marked on the x-axis and the percentage of results is marked on the y-axis. From the figure, it is evident that KFSVM has better performance in terms of precision, recall and f-measure than SVM [30] and Active Pruning Rules [31]. KFSVM applies predicted output as input for estimating the class label and this assists to achieve better results.

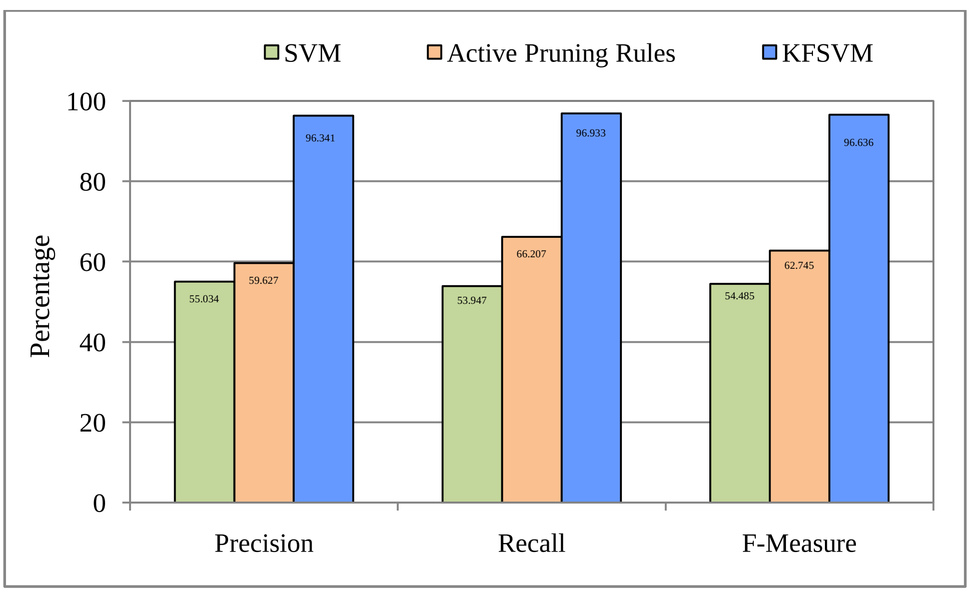

Figure 6. Children Dataset vs Precision, Recall, F-Measure

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Analysis of Adolescent Dataset for ASD

In Figure 7, the variables TP, TN, FP and FN are marked on the x-axis and the y-axis is marked with the count of records. It is very clear to understand that KFSVM has better performance against previous algorithms namely SVM [30] and Active Pruning Rules [31] in terms of TP, FP and FN. But, while noticing TN it is found that Active Pruning Rules [31] has a minor level better performance than KFSVM. The prediction phase and the updation phase in KFSVM assist better results in predicting ASD.

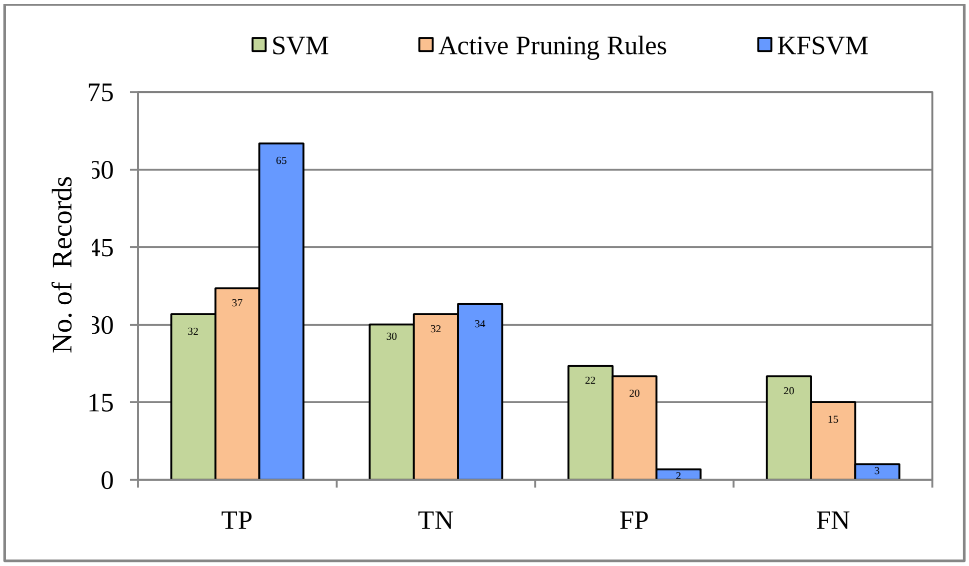

Figure 7. Adolescent Dataset vs TP, TN, FP, FN

In Figure 8, the performance metrics Sensitivity, Specificity and Accuracy are marked on the x-axis and the percentage of results is marked on the y-axis. From the figure, it has been observed that KFSVM has outperformed the other two algorithms namely SVM [30] and Active Pruning Rules [31]. The linear model present in KFSVM assists the classifier to perform better classification. SVM [30] and Active Pruning Rules [31] would have ignored the significant features and this result in poor classification.

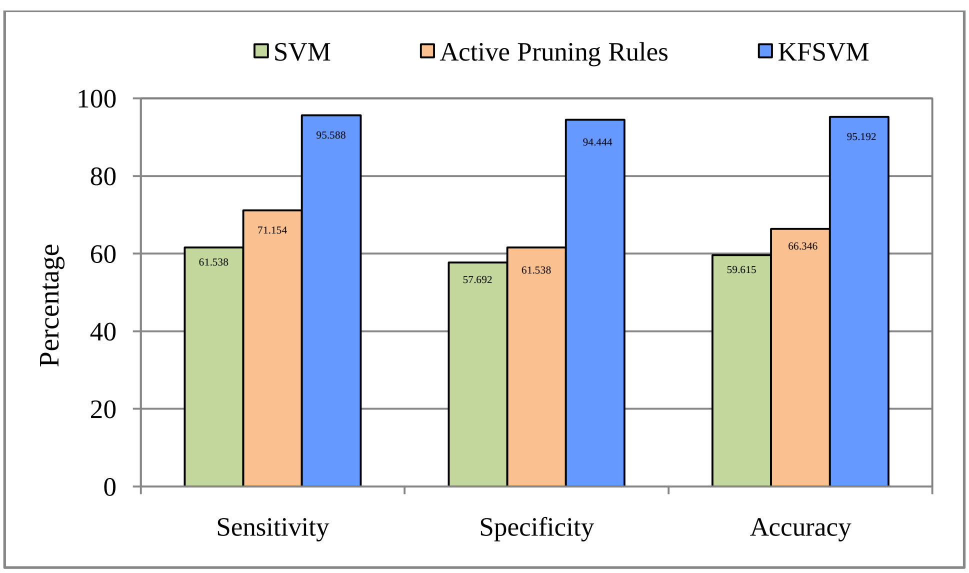

Figure 8. Adolescent Dataset vs Sensitivity, Specificity, Accuracy

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In Figure 9, the performance metrics Precision, Recall and F-Measure are marked on the x-axis and the percentage of results is marked on the y-axis. From the figure, it is evident that KFSVM has better performance in terms of precision, recall and f-measure than SVM [30] and Active Pruning Rules [31]. KFSVM applies predicted output as input for estimating the class label and this assists to achieve better results.

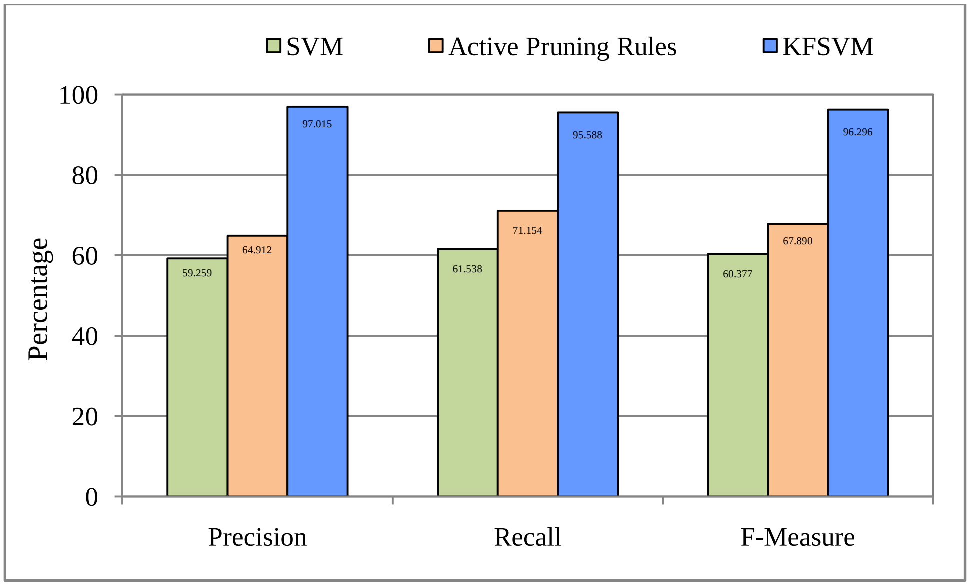

Figure 9. Adolescent Dataset vs Precision, Recall, F-Measure

Conclusion

This paper has proposed Kalman Filtering based Support Vector Machine (KFSVM) to predict Autism Spectrum Disorder (ASD) more accurately. To effectively classify the ASD, KFSVM ensembles two different algorithms namely Robust Kalman Filtering based Neural Network and Adaptive Support Vector Machine. Three benchmark datasets has been chosen to evaluate the performance of KFSVM against previously available algorithms for the prediction of ASD. Benchmark metrics are used to measure the performance of KFSVM. Results make an indication that KFSVM has better performance in predicting ASD than other algorithms. Future dimension can be focused to increase the classification accuracy by utilizing optimization algorithms.

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