SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V11I12P112

Volume 11 Issue 12, 123-134, December 2024

Original Article

Autism Detection Using Xception-based CNN with SVM on Resized and Normalized Neuroimaging Data

V. Hema[1], S. Gowri[2]

[1,2]*Department of Computer Science and Engineering, School of Computing, Sathyabama Institute of Science and Technology, Chennai, Tamilnadu, India.*

Received: 17 October 2024 Revised: 21 November 2024 Accepted: 10 December 2024 Published: 30 December 2024

Abstract *- A complicated neurological disorder known as Autism Spectrum Disorder (ASD) causes a variety of signs and behaviors. For prompt assistance and treatment, a prompt and correct diagnosis of ASD is essential. The deep learning model built on the Xception platform paired with Support Vector Machines (SVM) using MRI data is a unique method for diagnosing and identifying ASD presented in this paper. The first step of the suggested technique is preparing neurological data, including magnetic resonance imaging (MRI) and functional magnetic resonance imaging (fMRI), through downsizing and normalisation to improve extracting features and lower computing costs. Following this, the Xception-based Convolutional Neural Network (CNN) automatically extracts basic features from brain imaging information. The CNN model performs exceptionally well at identifying elaborate trends and differentiating between those with ASD and those who are usually developing. SVM is applied to the retrieved features to improve accurate classification and the ability even more. This novel technique uses SVM's ability to discriminate and deep learning's capability in feature extraction. The suggested technique achieves outstanding accuracy, sensitivity, and specificity in ASD identification and identification, as demonstrated by research results on a large dataset. On scaled and normalized brain data, the combination of Xception-based CNN and SVM shows promise for accelerating early detection of ASD and enhancing knowledge of the neurological basis of this complex condition. This study lays the door for more accurate and obtainable tools for medical practitioners to help with the early detection and treatment of ASD, thereby improving the standard of life for those who are impacted by this disorder. The proposed Xception-CNN with SVM-Lagrangian Optimizer obtains a remarkable accuracy measurement of 95.13 %.*

Keywords *- Autism Spectrum Detection, Xception Model, Convolutional Neural Network, Support Vector Machine, Normalization.*

1. Introduction

Autism is a complicated neurological illness that impacts a person's social life, interpersonal skills, and behavior. It is also known as autism spectrum disorder (ASD) or just autism. It is known for having a broad variety of signs and degrees of severity, thus the name "spectrum." ASD often appears in infancy and persists over an individual's lifetime; however, early assistance and intervention can greatly enhance results. The basic characteristics of autism include difficulties with socializing, such as problems establishing and sustaining ties, understanding and interpreting social cues, and communicating in a way that reciprocates.

Additionally, people with ASD might exhibit strong passions, repetitious behaviors, and a fondness for procedures. Patients with autism may have enhanced or reduced reactivity to sensory stimulation. Eye sensitivity is prevalent[1]. Since autism is such a diverse illness, studies on the root cause are still underway. It is thought that environmental and genetic variables influence its growth. In the past few years, there has been an almost steady rise in the overall incidence of ASD, which can be attributed in part to better understanding and clinical standards. For people with autism, early detection and treatment are essential since specialized assistance and treatments can enhance interpersonal skills, lessen problematic behaviors, and boost their general standard of life.

In order to gain [2]insight into the illness, create efficient therapies, and encourage a sense of belonging for people with autism in society, initiatives to raise autism awareness and conduct studies are growing. Autism Spectrum Disorder (ASD) identification is a method of locating people who could display behaviors or traits related to autism. Medical evaluations, behavioral findings, and occasionally specialized equipment and tests are commonly used in this diagnosis.

The purpose of ASD identification is to identify the illness as early so that patients and their carers can receive the proper therapies and care. Screening techniques [3]and surveys are frequently utilised for detecting individuals that might be vulnerable to autism, which is one of the key parts of ASD identification.

Diagnostic examinations, which frequently occur at checkups for kids, may include inquiries regarding the child's growth and behavior. Experts in the medical field, such as pediatricians, paediatricians, or behavioral experts, conduct a thorough diagnosis[4]. This evaluation may involve parent or carer screenings, in-person behavioral research, and standardized tests that evaluate interpersonal interaction, socialization, and routine behaviors. Since early support programmers can greatly enhance results for people with ASD, detection at an early stage of autism is crucial. According to research, initial treatment[5] can lessen the seriousness of some behaviors linked to autism while also assisting youngsters in developing their ability to interact with others. Speech practitioners[6], professionals in occupational therapy, and behavioral counsellors work together as part of an ASD identification team to thoroughly examine and assist with an individual's requirements. Technological advancements, such as neural networks and machine learning, have been investigated recently to help in autism identification[7]. Specialists have looked at the application of artificial intelligence and statistical analysis to find possible signs of autism in the looks on people's faces or their eye movements. To hone and enhance ASD detection strategies, continuing study is crucial. To gain insight into autism and provide more precise diagnostic tools, scientists are examining a variety of biological markers, a genetic variable, and firm approaches. The journey of people with autism and their carers begins with the discovery of ASD. Early detection and assistance specifically targeted to the person's requirements are made possible, thereby enhancing the individual's level of existence and socialization[8]. The majority of currently used techniques for diagnosing autism spectrum disorder (ASD) rely on tried-and-true diagnostics and screening tests that licensed practitioners and professionals frequently carry out. During well-child checkups, pediatricians [9] and other medical professionals frequently evaluate kid's stages of development. Additional evaluation for ASD may be warranted if there are any delays or departures from normal development habits. There are several standardized screening tools readily available to assist identify kids who may be susceptible for ASD.

Such belong to the Social Communication Questionnaire (SCQ) and the Modified Checklist for Autism in Toddlers (M-CHAT)[10]. Families or other carers frequently fill out these forms. Various experts, including pediatricians, pediatric neurologist, and behavioral specialists, are frequently involved in the official evaluation of ASD. This diagnosis [11]makes use of standardized testing techniques, including the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R), as well as deep talks with their parents or other carers and personal observations of the child's behavior. ASD-like signs can be linked to certain medical problems[12] and genetic variations. Medical examinations and genetic tests may be carried out to rule out potential deeper health concerns. ASD identification involves monitoring the child's behavior and evaluating socialization, expressive abilities, and repetitive behaviors. Experts search for distinctive patterns and behaviors. In order to better recognize the neural-related elements of ASD, neuroimaging approaches like magnetic resonance imaging (MRI) or functional MRI (fMRI) might occasionally be employed to analyse brain anatomy and activities. The importance of prompts for kids with suspected or known ASD cannot be overstated. The techniques[13] used include behavioral therapies, physical therapy, communication therapy, and others adapted to each individual's particular desire. By sharing details about their kid's behavior, growth, and any worries they might be experiencing, parents and other carers play a crucial part in this detection procedure. Instructors and trainers may observe the behavior and interactions of a kid in the educational setting, and this information can be very helpful.ASD discovery[14] is an ongoing procedure, so at-risk kids may be watched over time to follow their growth and spot modifications or additional signs. As a result, the testing process is customized to each person's specific requirements and traits. To improve outcomes and give people with ASD and their families the assistance and assets they need, early detection and treatment are still essential.

The Key contributions of this research are:

- To ensure to diagnose and categorize Autism Spectrum Disorder (ASD), this work offers a unique hybrid strategy that combines an advanced deep learning model, Xception-based CNN, with Support Vector Machines (SVM). The advantages of both deep learning and conventional machine learning methods are combined in this hybrid structure.
- The study concentrates on the downsizing and normalization of neuroimaging data, including magnetic resonance imaging (MRI) and functional MRI (fMRI). This preprocessing procedure improves the input data, making extracting features easier and less difficult to handle.
- A notable addition is using the Xception framework for feature extraction from neuroimaging data. Since brain imaging images may be extremely rich and subtle, Xception is recognized for its ability to identify complicated trends in complicated data.
- The retrieved features and Support Vector Machines (SVM) integration improve the model's identification precision and clarity. SVM makes an important enhancement to the accuracy of the ASD diagnosis since it is especially effective at differentiating between those with ASD and those who are usually functioning.
- The proposed method's performance is rigorously evaluated on a comprehensive dataset, demonstrating its effectiveness in accuracy, sensitivity, and specificity in ASD detection and classification. This thorough evaluation ensures the reliability and generalizability of the model.

- The study helps to create tools that are easier to use and more accurate for medical practitioners to diagnose ASDs early on. This might result in earlier treatments and better results for people with ASD.

The rest of the study is structured as follows: Section 2 reviews the existing research on detection problems employing various optimization strategies. In Section 3, problem statements were discussed. The suggested approach is described in Section 4. System models developed theoretically are provided in Section 5, which discusses the performance review. The study's conclusion is discussed in Section 6.

2. Literature Works

The investigation[15]explores the creation and assessment of AI algorithms for initial autism identification, demonstrating the ability to transform the accuracy of diagnosis. Three alternative approaches were investigated, using various AI algorithms and with differing degrees of effectiveness. The first technique combined extraction of features from a mixture of Local Binary Pattern (LBP) and Grey Level Co-occurrence Matrix (GLCM) methodologies with the capabilities of Feedforward Neural Networks (FFNNs) and Artificial Neural Networks (ANNs). Amazingly, this method produced a 99.8% accuracy rate, demonstrating the extraordinary potential of neural networks in identifying cases of autism. Utilizing prepared Convolutional Neural Network (CNN) models, particularly Google Net and ResNet-18, the second method centred on collecting deep traits. These models' impressive accuracy rates of 93.6% and 97.6%, respectively, highlight the effectiveness of deep learning in this situation. The third approach combined deep learning with machine learning using ResNet-18 and Google Net in two phases: CNN for extracting map-based feature information and SVM for classifications. This hybrid technique produced accurate diagnostic scores for Google Net + SVM and ResNet-18 + SVM of 95.5% and 94.5%, respectively. This emphasizes the benefits that may be achieved by combining several AI approaches. This research possesses several drawbacks, chiefly the lack of medical testing and assessments on more significant and more varied test groups, even if these findings highlight the promise of AI in increasing early autism diagnosis. Although these results are beneficial, they also highlight the necessity for more clinical testing and real-world application to realize the method's promise in clinical environments fully.

During the lack of a proven treatment, the difficult issue of early autism spectrum disorder (ASD) identification was taken on by this study. The investigation [16]began with a broad objective of collecting substantial ASD datasets that included people of all ages, including babies and adolescents. The investigators used a variety of data transformation approaches, such as sine, logarithmic, and Z-score algorithms, to improve the usefulness of the dataset. All ages had varied tastes throughout the thorough categorization of the adjusted datasets using a number of algorithmic learning techniques. Adaboost for toddlers, Gumboots for kids, Support Vector Machines (SVM) for teens, and Adaboost for adults were shown to be the best accurate classifiers. The relevance of adapting predictive strategies for various aged populations for the best ASD identification is highlighted by those results. In particular, this research emphasized the effectiveness of Z-score changes for kids and teens and the potential of sine function improvements for babies.

Furthermore, researchers effectively discovered major ASD risk factors among these age groups by using information filtering to Z-score modified datasets, providing insight into potentially early markers of the illness. The promise of machine learning techniques in detecting the earliest signs of ASD is generally highlighted by this study. It emphasizes that, additionally to the absence of a proven cure, these methods may produce accurate diagnoses of ASD, assuming the right optimization. To improve the detection of ASD and awareness of linked neurological disorders, it does accept the need for more reliable records and a thorough examination of pertinent components. In conclusion, the research is important in improving early ASD identification by leveraging machine learning technology. The consequences of such advancements include the possibility of enhanced treatments and services for people with autism, highlighting the paradigm-shifting significance of this study for the identification and treatment of ASDs.

Due to the growing understanding of the need of early detection and therapy, there have been considerable breakthroughs in the detection and categorization of autism spectrum disorder (ASD). Past studies have emphasized the necessity for quick and precise classification techniques that allow ASD patients to get care when needed. Since machine learning approaches can automate the evaluation procedure, they have become increasingly popular in ASD studies. As demonstrated in this work, using varied datasets from a range of age categories is now a common strategy for improving classification algorithms' durability and generalization ability. In the framework of diagnosing ASDs[17], machine learning techniques like K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forests (RF) are widely investigated.SVM, renowned for its capacity to manage complicated and highly dimensional data, has demonstrated progress in earlier studies. The importance of establishing the dependability and durability of ASD detectors is highlighted by the focus on recurrent selection and meticulous assessment, as carried out in this work. The RF strategy's astonishing nearly 100% accuracy is a significant milestone that highlights the possibilities of machine learning systems when given large, well-organized information. Until these autonomous diagnosing approaches can be used in a medical context, it is crucial to recognize the desire to receive additional clinical investigation and validation. The literature discussion concludes by highlighting the dynamic nature of ASD treatment, with an increasing focus on machine learning methods and the need for prompt identification for better results. Although the efficacy of the RF technique is encouraging, it should be seen as an addition to, not a substitute for, clinical evaluation and exam in the identification of ASD. To solve the practical problems and guarantee the moral and trustworthy utilization of machine learning in ASD treatment, more study is required.

In recognition of the effective use of large-scale data tools, the research of Autism Spectrum Disorder (ASD) [18]has undergone a dramatic transition in the past decade. Despite the fact that ASD studies are still following other disciplines in using such options, current developments in data gathering and analysis technology have opened the door for an exciting time in this subject. The number of research using machine learning approaches to investigate ASD, uncover its neural roots, and create better therapies has significantly increased, according to experts. This evaluation of the current literature comprehensively analyses 45 papers that use autonomous machine learning techniques for ASD. The research studies use various methods, such as analyzing texts and classification, which considerably add to the body of research in this area. The main goal of this study is to recognize and explain new developments in machine learning benefits for ASD investigations, with a final aim of assisting and educating investigators in creating reliable and technically sound approaches for handling Autism-related data. It could be vital to recognize this method's drawback, though. Analyzing texts can reveal new relationships and linkages but cannot provide proof or confirmation for such findings. Thus, Upcoming experiments will be crucial in validating the conclusions drawn from machine learning-driven assessments. This phenomenon is developing in machine learning and ASD study, which is exciting for gaining greater awareness of the complexity of the illness and, lastly, enhancing our knowledge of and ability to manage ASD successfully.

This investigation[19] suggests a novel method for diagnosing Autism Spectrum Disorders (ASD) using face feature identification and electronic data. Techniques for deep learning have perspective, but this study emphasizes the necessity for precise tools to collect and analyse face data. The research creates an accessible website that utilizes advanced learning technology to accomplish this objective and offers beneficial resources for communities and professionals. This system uses the Flask framework and a convolutional neural network using transfer learning capability. To overcome the difficulty of classifying ASD according to face traits, the investigation uses trained algorithms, including Xception, Visual Geometry Group Network (VGG19), and NASNETMobile.2,940 face pictures collected from the Kaggle site make up the data collection. This research uses precision, reliability, and susceptibility indicators to gauge how well such deep-learning algorithms perform. Particularly, the detection rate for the Xception model is 91%, preceding that for VGG19 and NASNETMobile at 80% and 78%, respectively. These findings highlight the possible uses of identifying faces and deep experiences in modern media-based autism assessment. The rather small collection of 2,940 face pictures that might not completely represent the range of face characteristics needed for effective autism detection is a weakness of this investigation. Considering this drawback, the results imply that face detection and deep learning are promising strategies for detecting ASD on social networking sites. More studies using more complex and varied facts may improve the durability and dependability of this means of analysis.

The proposed crucial requirement for prompt detection of Autism Spectrum Disorder (ASD) is addressed in this paper [20]by addressing the shortcomings of the current pricey and arbitrary expert-based screening techniques. It combines clinical information, notably electroencephalography (EEG), with behavioral data focusing on the eyes and vocal trends. It presents a unique machine learning technique for identifying ASD in kids. Modern feature extraction methods are used to retrieve appropriate information through different databases. The study also presents a novel integration method that employs categorized naive Bayes and achieves a remarkable predictive efficiency of 87.50%. The resulting results highlight the usefulness of the above machine learning approach for prompt ASD identification. This research illustrates that visual fixing, facial movements, and EEG recordings for each exhibit various levels of biased ability for separating ASD compared to usually growing kids, with EEG resulting as a particularly successful finding characteristic by means of an in-depth evaluation utilizing matrix structures and visualizations. This study emphasizes how combining neural and behavioral data may considerably improve categorization ability. This research marks a significant improvement in the creation of accurate and affordable strategies to facilitate early ASD detection by overcoming the shortcomings of currently used clinical approaches. It is crucial to recognize the study's limitations, which include the collections' absence of random features and changes in gathering circumstances. This restriction necessitates more study in order to develop ASD identification techniques that can take into consideration the variations seen on multiple occasions and under various conditions. However, the results of this investigation show considerable potential for enhancing early identification and therapy for people with ASD, which may result in more efficient therapies and care.

In this inquiry, three different AI techniques to perform early autism diagnosis are investigated and evaluated. The basic approach makes use of neural network technology, especially artificial neural networks (ANNs) and neural networks with feedforward architecture (FFNNs)[21], and achieves an impressive precision rate. Combining attributes through another technique using local binary pattern (LBP) and grey level co-occurrence matrix (GLCM) approaches allows for this staggering precision. In order to attain excellent precision rates of 93.6% and 97.6%, this research uses prepared convolutional neural network (CNN) models like GoogleNet and ResNet-18.Deep identification of features using such models demonstrates their usefulness during initial autism detection. The third approach presents a two-block approach that blends deep learning algorithms with machine learning strategies, notably Support Vector Machine (SVM), using GoogleNet and ResNet-18. Clinical accuracy values for this method are 95.5% for GoogleNet + SVM and 94.5% for ResNet-18 + SVM. This approach uses SVM for classification, whereas CNN is applied to get mapping features. The results demonstrate the outstanding effectiveness of all three techniques and their ability to serve for therapeutic use in identifying early signs of autism. Though the reliability of combining characteristics from CNN models, LBP, and GLCM techniques is encouraging, technical difficulties may slow down analysis and make the combined features less useful for medical contexts. Such artificial intelligence techniques have outstanding reliability rates, but to enable their easy incorporation into medical practice, further studies might focus on computational effectiveness issues. Nevertheless, such results represent a substantial advancement in the use of AI technologies for the early recognition of autism, which might result in earlier therapies and enhanced results for people with autism.

3. Problem Definition

The issue of being necessary for a precise and prompt identification of Autism Spectrum Disorder (ASD) has been discussed in a variety of study investigations. Previous ASD diagnostic techniques are occasionally costly and depend on arbitrary professional assessments, which causes lags in finding and assisting ASD patients. Such studies seek to improve earlier evaluations for ASD and diagnostic procedures by utilizing machine learning[18]and artificial intelligence (AI) technologies. In order to analyse a variety of collected individuals, such as face characteristics, behavioural data, and EEG data[19], researchers investigate several AI methodologies, such as neural networks, convolutional neural networks (CNNs), and machine learning techniques. The investigations emphasize the difficulties and restrictions related to computational effectiveness and the necessity of additional medical verification and practical usage, even if these techniques appear to have a good chance of obtaining excellent accuracy. In general, the study aims to revolutionize the detection and management of ASD, which may result in enhanced results and care for people with autism spectrum disorders.

4. Autism Detection Using Xception-based CNN with SVM Framework

Employing the ABIDE dataset, this thorough workflow for classifying autism begins with data preprocessing, which includes dealing with missing values by means of imputation, reducing class imbalances with SMOTE, and normalizing the results. Following feature extraction and selection, the Xception pre-trained neural system is used to uncover specific trends from brain scan data. A convolutional neural network (CNN) is probably used to choose additional characteristics. In order to create reliable prediction designs, Random Forest (RF) and Support Vector Machine (SVM) classifications are then used to improve characteristics for autism categorization. To improve the precision and practicality of autism diagnosis predicated on the ABIDE dataset, this multimodal strategy integrates feature design, data collection, and machine learning approaches.

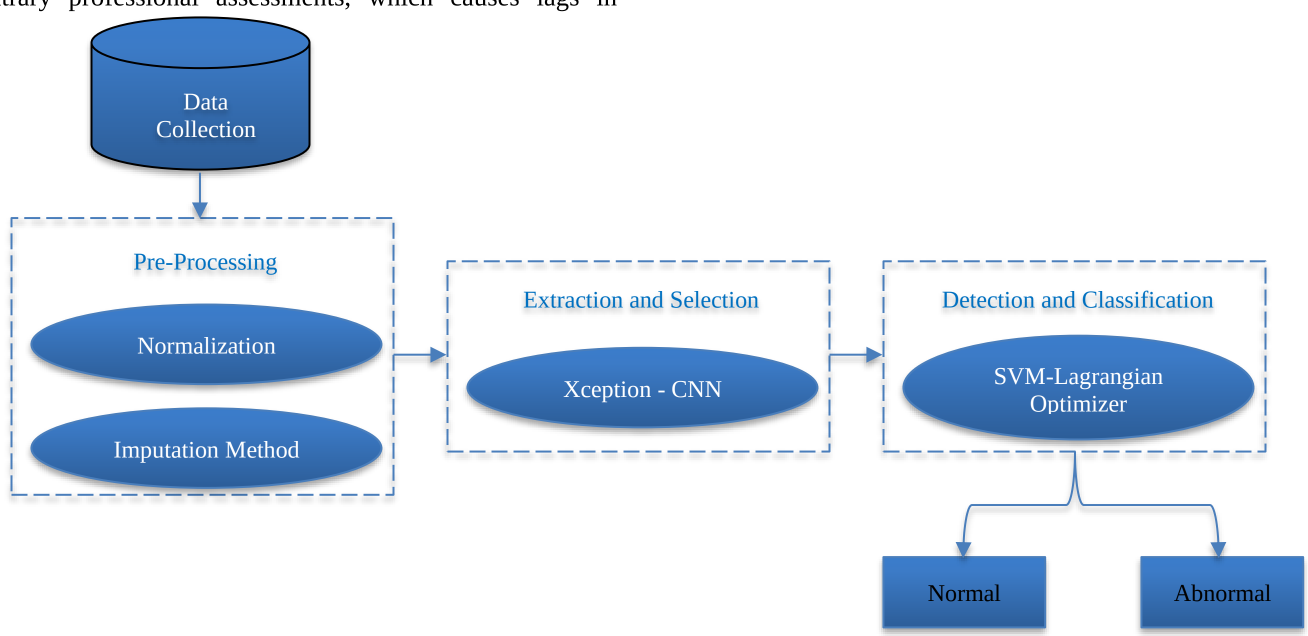

Fig. 1 Framework of Autism Detection Using Xception-based CNN with SVM-Lagrangian Optimizer

4.1. Data Collection

This research aimed to use neural networks with deep learning to distinguish individuals who have autism spectrum disorder (ASD) and controls using just the patients' brain activity characteristics. Researchers examined brain imaging results from individuals with autism spectrum disorders that were collected from ABIDE (Autism Brain Imaging Data Exchange), a global multi-site collection. Social issues and recurring behaviors are hallmarks of ASD, a brain-based condition. One in every 68 kids around the United States has ASD, based on current statistics from the Centers for the Prevention and Control of Disease. Therefore, I looked at the functional connections and structures that may be used to categorically classify people with ASD using neurological imaging data, along with trying to understand the neural networks that resulted from the diagnosis. By correctly identifying 70% of ASD sufferers in the sample vs control patients as well, the outcomes raised concerns about the state of the art.

The classification's characteristics revealed an anticorrelation among the activity of the nervous system's front and rear lobes, which is consistent with the scientific evidence currently available on the impairment of prior-posterior connection in ASD. Also, report the findings and highlight the neural regions that, according to the deep learning approach, were particularly important in distinguishing ASD from developing normal control mechanisms.[22]

4.2. Data Preprocessing with Missing Value Imputation and Normalization

4.2.1. Normalization

The dataset has been subjected to data standardization to lighten the network's computational load. The position coordinates, x, y, and z, are normalized using a Min-Max method [23]to the range [0, 1]. The ability of the network to converge is improved by using Max-Min normalization and learning bounded objectives. The basic data preparation technique of min-max normalization guarantees that the numerical characteristics or parameters are adjusted to a particular range, often between 0 and 1.

In order to improve the suitability for analysis and target detection algorithms, raw data values must be standardized in this procedure. By aligning the data into the algorithms' desired input range, min-max normalization increases the efficiency and precision of the techniques. By moving these outliers closer to the top or lower boundaries of the normalized range, Min-Max normalization may assist in highlighting them and make them easier to differentiate from regular traffic patterns.The initial data set is transformed linearly by the Min-Max normalization approach. When some characteristic's minimum and maximum values are normalized using the Min-Max formula, the initially set value of the attribute gets replaced with the value within the interval$[0,1]$. The formula is given in Eqn. (1):

$$X'' = \frac{X-Min}{Max-Min} \tag{1}$$

Where Min and Max are the minimum and maximum values of typical X'', accordingly, the initial value of X is changed by Min-Max normalization to the value in the range $[0,1]$.

4.2.2. Missing Value Imputation

Many values are lacking. The investigation of data is used in this stage to find rare cases and treat them utilizing the box chart method. Data collection had a number of values that were lacking; thus, a progressive imputer was used to manage issues[24]. The ability to employ as many test results as feasible for predictive purposes improves the data entry technique, which is preferable overall. An example of a situation where repetitive imputation methods are used is a predictive issue whereby lacking values are anticipated. In contrast, each parameter is formed as an expression of the remaining features. Employing the progressive missing value elimination approach, every single characteristic haveinstances following the absence of importance computation, so all missing values are eliminated.

4.3. Feature Extraction and Selection by Xception-based CNN

A complex CNN that presents an additional inception layer is called the Xception. A point-by-point convolution stage comes after the depthwise convolution phases, which make up the inception layers. In this work, the prior approach[19], which had been developed on a typical dataset, was utilised in the extracting of features approach for obtaining the features coming from the newly generated data set and to eliminate the most significant levels of the framework. In order to perform specific categorization depending on the variety of categories, additional outermost layers have been added to the system. To prevent overwriting, the standard features have been fine-tuned to fit a specific class.

The neural network utilised in the Xception framework structure to extract the picture characteristics for this data set is seen in Figure 2. The characteristic maps were employed in the Xception design, which also included two extremely dense layers with rule activation characteristics, which were 128 and 64 layers thick and included a worldwide max pooling structure. The flattened layer, which typically accepts a features map as a source and produces vector data as an outcome, was subsequently given the outcome of the thick layers. The final result was improved by sequential normalization, which prevented excessive fitting. The early-stopping strategy, which halted the training process when the prediction's rejection rate did not decrease, was aided. The Softmax function was employed as the final layer for outcome forecasting. Convolutional Neural Network (CNN) is an approach to deep learning used to create predictions for various issues. A neural network [25]with a feedforward structure that finds inspiration from how humans think. A single input layer, a single output layer, as well as several more layers, such as convolution layers, max pooling, fully connected layers, and normalization layers, are all included in a CNN structure. Using the multiplication of matrices and the bias adjustment thereafter, the activation of those characteristics may be calculated.

The term "max pooling"[26] refers to a merging process that chooses the largest component within the feature map area and the filtering process covers. The result of the max-pooling layer would consequently be a map of characteristics that included the most prominent characteristics from the prior feature map. Every single layer in a CNN is constructed from the layer before it. The translation constancy means that even when accidentally converting or slightly modifying the input, the outcomes of most pooled outcomes remain unchanged. This research concludes that CNNs may effectively classify image-driven data incorporating autistic movements/pictures of diagnostic features. CNNs have been proven resilient to tiny alterations in feature maps supplied and assist in focusing on a more compact feature map. This is crucial since not all photos or films have the same geographical or locational characteristics. In order to better classify data pertaining to autistic individuals, models based on deep learning have to be further investigated to represent all of their distinctive qualities accurately. The CNN component was then updated to include 3-dimensional tensors for training. CNN utilised the kernel that performs convolution to carry out the same given processing on the input data. Each subsequent place in the sequence might find correlations discovered at the first location. By having each successive convolution layer frame get bigger, the suggested network employed the three convolution layers to introduce the dimension filter's unique organisational design.

Additionally, the Rectified Linear Unit (RELU) can cause some neurons to cease their activity, which made it possible to accomplish a certain level of network architecture sophistication reduction. By down-sampling, the max-pooling layer was employed to uncover the most valuable distinguishing traits while further reducing the likelihood of an over-fitting. The following was accomplished by compressing the data to remove less-useful parametric data while retaining more-useful information. The CNN learning step was rendered useless since the initially generated time-series model was susceptible to progressive vanishing.

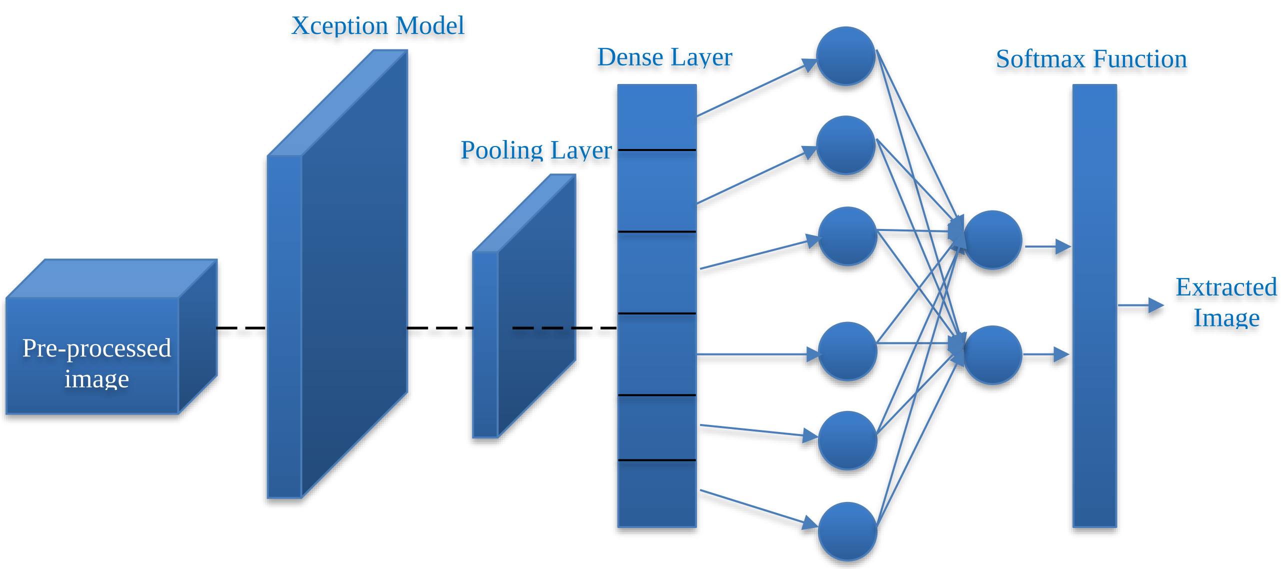

Fig. 2 Extracting features by Xception-CNN

4.5. Autism Detection and Classification by SVM with Lagrangian Optimizer

4.5.1. Support Vector Machine with Lagrangian Optimization

SVM is a supervised classification method that employs lines of data to discriminate among two distinct categories. The process of separation can be complicated in numerous situations. By the present instance, known as Kernel[27], the outermost dimensions is required to be changed beyond 1 to the Nth dimension. It refers to the physiological link across the two findings, which puts it differently. This research employed a support vector machine (SVM) for categorization[28]. Finding the separation referred to as using the greatest excess separation across classifications in the feature domain is the fundamental goal of collection that fits for SVM to partition occurrences of both categories equally as feasible. The supportive vector analysis, which is the nearest data point, is what the hypersurface focuses on. SVM is a popular approach for solving both linear and non-linear category problems in classification and identifying the ideal hyperspace that maximizes flexibility, whereas minimizing the level of inaccuracy is the goal of SVM for binary categorization. The Lagrange framework may be used to obtain the SVM parameters. Frequently, an SVM's decision-making process is described below in Equation (3):

$$f(x) = sine(w^T \bullet x + b) \tag{3}$$

Where $f(x)$ Represents the predicted class label, x is the input data, $w$is the weight vector, b represents the bias term,$sine$ is the function, it gives positive values a return of +1 and negative ones a return of -1. The margin is the angle across the support vectors and the selected border (hyperplane). The following calculation to increase the margin is described in Equation (4),

$$Margin = \frac{2}{\|w\|} \tag{4}$$

Where $\|w\|$ denotes the Euclidian norm (magnitude) of w. Finding w and b that maximizes the margin when adhering to specific limitations is the goal of SVM. The following is commonly accomplished by employing multipliers from Lagrange to solve a restricted optimization issue. The goal parameter is maximized as given in Equation (5),

$$L(w, b, a) = \frac{1}{2} \bullet \|w\|^2 - \sum[a(i) \cdot (y(i) \cdot (w^T \cdot x(i) + b) - 1)] \tag{5}$$

Where a Lagrangian function is denoted as$L(w, b, a)$, Lagrange multipliers are $a(i)$, $y(i)$ is the class label of thei^{th} data point, $x(i)$ is the i^{th} data point. In general, the optimization problem's parameters are represented in Equation (6),

$$\sum[a(i) \bullet y(i)] = 0, a(i) \geq 0 \tag{6}$$

These requirements assure that the selected margin is an ordered set of support units and that the multipliers obtained from Lagrange are not negative. It is common practise to restructure the optimization problem into its duality form, which facilitates the calculation of the multipliers based on Lagrange $a(i)$Furthermore, it optimizes the solution. Using the Lagrange multipliers, one may determine w as follows in Equation (7),

$$w = \sum[a(i) \bullet y(i) \bullet x(i)] \tag{7}$$

A support vector (the data point relative to the margins) with$a(i)$, higher than zero may be used to determine the bias factor$b$is given in Equation (8),

$$b = y(i) - w^T \bullet x(i) \tag{8}$$

5. Results and Discussion

A thorough data processing and classification structure was utilised in the ABIDE dataset's overall framework to distinguish between normal and disordered brain imagery. In the preprocessing stage, crucial procedures, including normalisation and SMOTE (Synthetic Minority Over-sampling Technique), were carried out to solve class imbalance and missing value imputation to guarantee the data quality. In order to get the collected data ready for further analysis, several preprocessing procedures were essential. The Xception Convolutional Neural Network (CNN), an efficient design to extract high-level characteristics concerning neuroimaging records, was used for feature extraction with selections. The capacity of Xception to recognise intricate structures in brain imagery was used to develop a selective set of features. A Support Vector Machine (SVM) with Lagrangian multiplier optimization was used to conclude the categorization challenge. Focusing on the collected characteristics, SVM performed well as a classifier to distinguish from normal and pathological brain imagery. SVM was a good choice for this assignment because of its capacity to manage multi-dimensional data and identify the most effective limits. The categorization of brain images using this paradigm produced encouraging results. In order to distinguish between pathological and normal brain imagery, the preprocessing methods, feature extraction using Xception, and SVM classification methods were used. This strategy might greatly aid findings and awareness of neurological diseases, which can also enhance therapeutic uses and neuroimaging studies. The design would be necessary to prove its efficacy and dependability in practical situations by additional analysis and verification of larger records and medical specialists' involvement.

5.1. Experimental Outcome

Figure 3 depicts training accuracy and training loss. Since training moves through epochs, the training accuracy and training loss for the Autism Spectrum Disorder (ASD) detection system shows a distinct pattern. The model continuously performs better, starting with an initial training accuracy of 0.1 and a training loss of 0.93 at epoch 1. By epoch 17.5, when training accuracy had reached 0.94, it was clear that the model was becoming better at correctly categorizing ASD cases. The training loss gradually declines during the same time frame, going from 0.93 to 0.6. This decrease in training loss further supports the model's ability to learn and its enhanced performance in identifying ASDs by showing that the model successfully minimises the error among its estimations and the reality of the data.

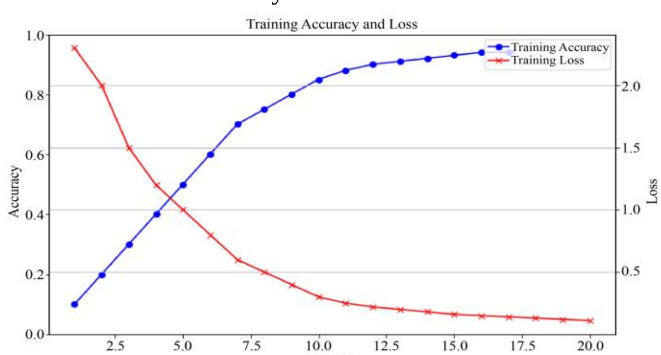

Fig. 3 Training accuracy and training loss

The Autism Spectrum Disorder (ASD) detection system's testing accuracy and loss have a distinctive trend over time. The framework exhibits a testing accuracy of 0.1 and a testing loss of 0.93 at the starting epoch (1). Accuracy and loss show a distinct pattern as training goes on. The model's testing accuracy rises progressively, peaking at 0.94 by epoch 17.5, demonstrating its high capacity to identify ASD cases in unidentified data. Testing loss also falls from 0.93 to 0.6, demonstrating the model's ability to reduce prediction mistakes. But at epoch 17.5, testing loss suddenly increases till it reaches 1.23, which raises the possibility of adapting to the training data. A thorough assessment of regularization approaches or system variations could be required to continue strong generalisation efficiency. Figure 4 Testing Accuracy and Testing Loss.

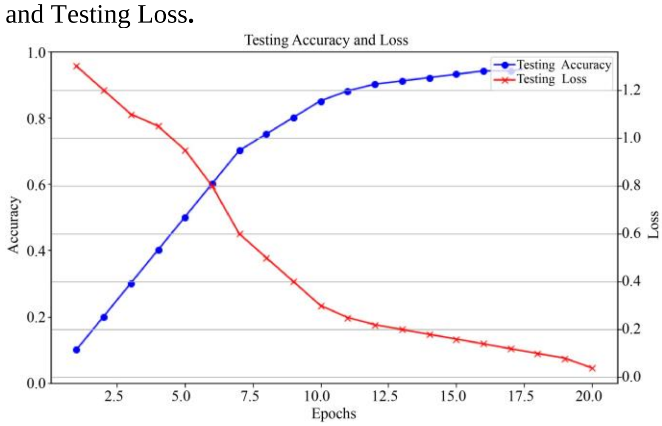

Fig. 4 Testing accuracy and testing loss

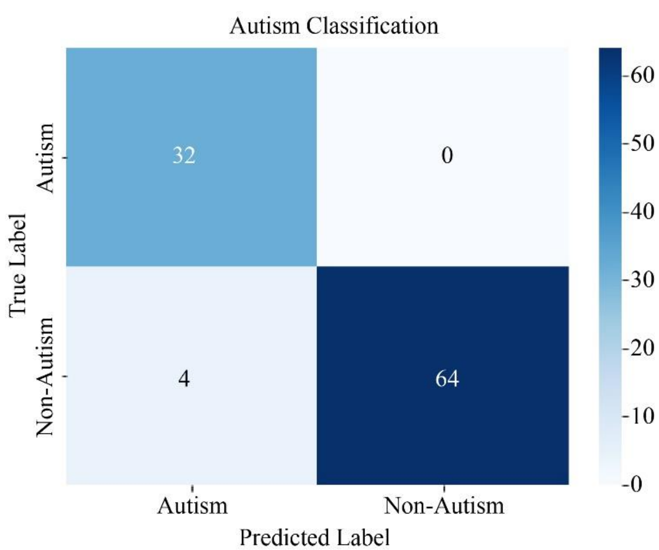

Fig. 5 Confusion Plot for ASD Clasification

The confusion matrix plot, as shown in Fig. 5, which is used to classify autism, shows how well the system is able to differentiate between the two classifications of "Autism" and "Non-autism." Fig. 4 Testing Accuracy and Testing Loss. The data matrix demonstrates that there were 4 occasions where the real label was "Autism," the system accurately identified these accordingly (true positives). Furthermore, the system accurately recognized 64 cases where the real label was "Non-autism" (so-called true negatives). 32 cases still had the proper label of "Autism," though the system incorrectly projected it to be "Non-autism" (false negatives).

However, the system never made a "Non-autism" prediction that was "Autism" (false positives). The confusion structure offers important insights into the model's efficacy, emphasizing its moderate accuracy in properly recognizing "Non-autism" instances. However, it may still need to be improved in order to identify "Autism" cases, as seen by the quantity of false negatives.

5.2. Performance Evaluation

This study represents accuracy, precision, recall and F1-score for performance measurement as represented in Equation. (9) to Eqn. (12) are depicted as follows:

5.2.1. Accuracy

It calculates the fraction of real outcomes, including true positives and true negatives, across all cases investigated. It is expressed in Equation (9),

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + Fale\ Negative} \quad (9)$$

5.2.2. Precision

The ratio of exactly anticipated positive outcomes to overall predicted positive occurrences is defined as precision. The precision is calculated using Equation (10)

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (10)$$

5.2.3. Recall

The recall measures the proportion of genuine positive samples that were projected to be positive. Using Equation (11), calculate the value recall.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (11)$$

FP represents false positive pixels, FN signifies false negative pixels, TP symbolizes true positive pixels, and TN represents true negative pixels.

5.2.4. F1-score

In the categorization task, recall and accuracy relate. Although a high value for both is ideal, the reality is generally great accuracy with low or high recall with low accuracy.

To account for both recollection and accuracy, the F1-score, which is a mean of recall and accuracy, can be employed. Equation(12) shows the definition of F1-score.

$$F1 - score = 2 * \frac{Precison * Recall}{Precision + Recall} \quad (12)$$

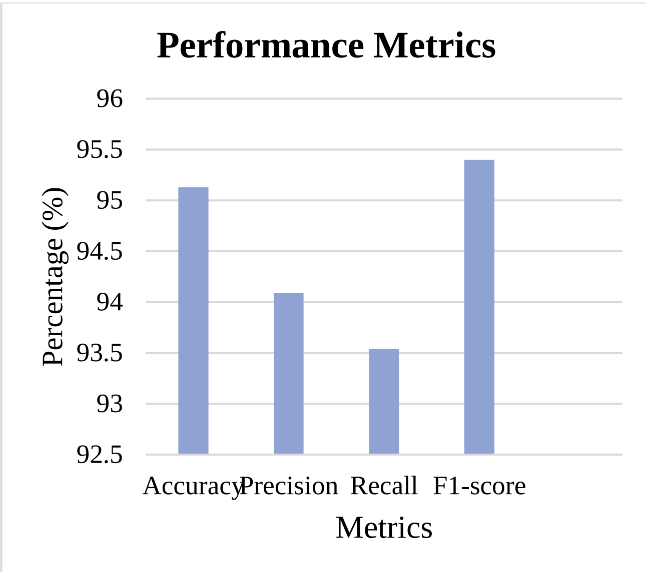

Fig. 6 ProposedXception-CNN with SVM-Lagrangian Optimizer

Table 1. Performance metrics of proposed method

ProposedXception-CNN with SVM-Lagrangian Optimizer	
Performance Metrics	**Values (%)**
Accuracy	95.13
Precision	94.09
Recall	93.54
F1-score	95.40

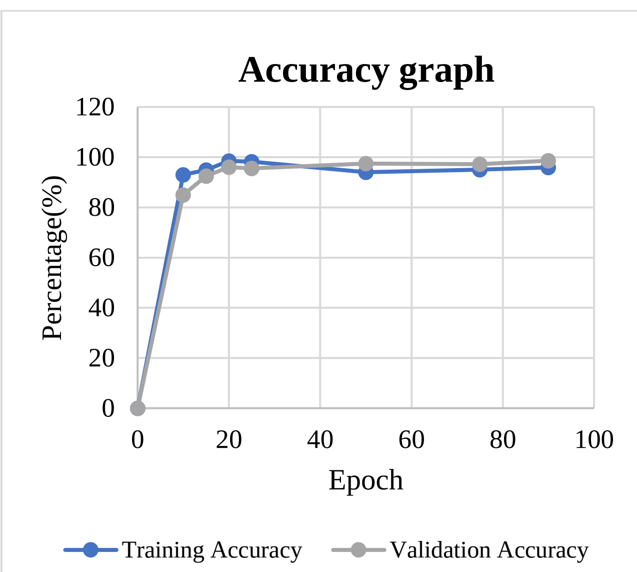

Fig. 7 Training and testing accuracy

Table 1 represents the performance metrics of the proposed method. The "Proposed Xception-CNN with SVM-Lagrangian Optimizer" approach performed exceptionally well through several significant efficiency criteria. It demonstrated its capacity to accurately categorise cases in the given assignment, with an accuracy of 95.13%. Additionally, the technique's competence in reliably detecting positive cases while minimizing false positives is indicated by the precision score of 94.09%. With an elevated recall score of 93.54%, it can recognize a significant number of real positive instances. Furthermore, the technique exhibits aharmony among recall and precision, earning a strong and successful method for identifying autism that achieves an amazing F1-score of 95.40%. These outstanding results indicate the method's appropriateness for its intended usage and ability to enhance reliable and precise findings considerably.

In Figure 7, the training and testing accuracy graph is depicted. Figure 8 graphically represents training and testing loss.

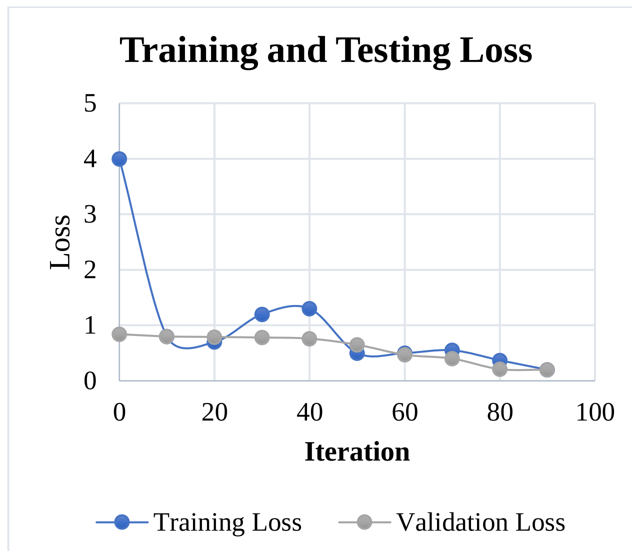

Fig. 8 Training And Testing Loss

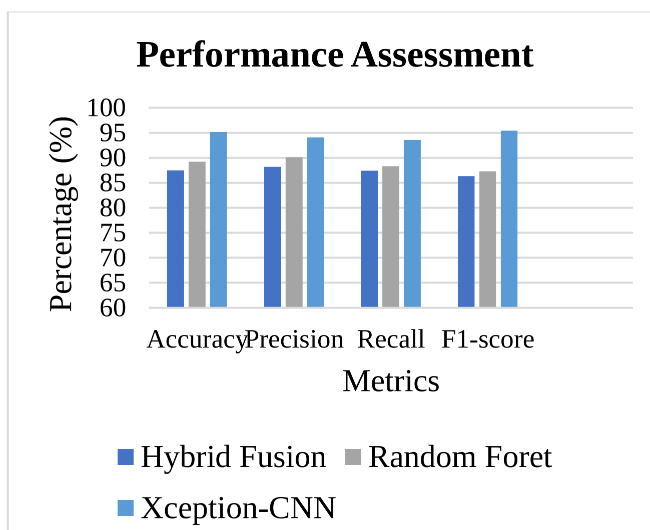

Fig. 9 Performance metrics

Figure 9 describes the performance metrics of the proposed method with those of existing methods.

Table 2. Performance metrics of the proposed method are evaluated with existing methods

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Hybrid Fusion[20]	87.50	88.20	87.4	86.31
Random Forest [29]	89.23	90.12	88.33	87.3
ProposedXception-CNN with SVM-Lagrangian Optimizer	95.13	94.09	93.54	95.40

Table 2 shows the Accuracy, Recall, Precision and F1-score of the proposed approach with existing methods. Three alternative approaches were assessed for performance in a particular job by comparing categorization methods. The "Hybrid Fusion" approach has an F1-score of 86.31%, an accuracy of 87.50%, a precision of 88.20%, and a recall of 87.4%. The "Random Forest" approach produced better results, with accuracy, precision, recall, and F1-score of 89.23%, 90.12%, 88.33%, and 87.3%, respectively. However, the proposed Xception-CNN with SVM-Lagrangian Optimizertechnique stood out in this investigation, achieving the greatest accuracy of 95.13%. Additionally, it had exceptional precision (94.09%), recall (93.54%), and an F1-score of 95.40%. These findings imply that the suggested technique improves the alternatives and shows the ability to tackle the problem at work. It integrates feature extraction by applying an Xception-CNN with classification using an SVM and Lagrangian optimizer.

6. Conclusion

The preprocessing methods of normalization and imputation to analyses have been used to improve the accuracy of the input data in detecting and classifying Autism Spectrum Disorder (ASD). By helping to scale the characteristics to a similar range, normalization makes sure the regression analysis is not biased to any particular variables. Imputation fills in the gaps left by missing data, enabling the model to use a whole dataset to judge. The Xception Convolutional Neural Network (CNN) is used for feature extraction. It demonstrates the capability to automatically extract complex patterns and structures from the input data, possibly improving the ability to differentiate of the model. Support Vector Machines (SVMs) have since been used to identify and categorise ASDs. SVMs are a good option for differentiating between ASD and non-ASD instances since they are well-known for their efficiency in binary classification tasks. This complete technique for precise ASD diagnosis and classification, which combines data preprocessing, feature extraction, and classification, is highlighted by this holistic approach. To confirm the model's generalizability, the model's performance has to be carefully assessed on different datasets. In recognition of more exact and reliable Autism Spectrum Disorder (ASD) identification and categorization in the near term, the task will also involve investigating sophisticated deep learning frameworks and incorporating multimodal data types.

References

[1] Dimitrios I. Zafeiriou et al., “Autism Spectrum Disorders: The Quest for Genetic Syndromes,” *American Journal of Medical Genetics Part B: Neuropsychiatric Genetics*, vol. 162, no. 4, pp. 327-336, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ian M. Shochet et al., “The Cooperative Research Centre for Living with Autism (Autism CRC) Conceptual Model to Promote Mental Health for Adolescents with ASD,” *Clinical Child and Family Psychology Review*, vol. 19, pp. 94-116, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[3] Esraa Tarek Sadek et al., “Computer Vision Techniques for Autism Symptoms Detection and Recognition: A Survey,” *International Journal of Intelligent Computing and Information Sciences*, vol. 20, no. 2, pp. 89-111, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Amanda D. Heidgerken et al., “A Survey of Autism Knowledge in a Health Care Setting,” *Journal of Autism and Developmental Disorders*, vol. 35, no. 323-330, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[5] Eleni Mitsea et al., “Metacognition, Mindfulness and Robots for Autism Inclusion,” *International Journal of Recent Contributions from Engineering, Science & IT*, vol. 8, no. 2, pp. 4-20, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Kristina Gasiewski et al., “Collaboration between Behavior Analysts and Occupational Therapists in Autism Service Provision: Bridging the Gap,” *Behavior Analysis in Practice*, vol. 14, pp. 1209-1222, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Fadi Thabtah, “Machine Learning in Autistic Spectrum Disorder Behavioral research: A Review and Ways Forward,” *Informatics for Health and Social Care*, vol. 44, no. 3, pp. 278-297, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Richard L. Moreland, John M. Levine, *Socialization in Organizations and Work Groups*, Psychology Press, pp. 1-44, 2001. [Google Scholar] [Publisher Link]

[9] "Identifying Infants and Young Children With Developmental Disorders in the Medical Home: An Algorithm for Developmental Surveillance and Screening," *American Academy of Pediatrics*, vol. 118, no. 1, pp. 405-420, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[10] David D. Schwartz et al., "Age-Related Differences in Prevalence of Autism Spectrum Disorder Symptoms in Children and Adolescents with Costello Syndrome," *American Journal of Medical Genetics Part A*, vol. 173, no. 5, pp. 1294-1300, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Latha Soorya et al., "Prospective Investigation of Autism and Genotype-Phenotype Correlations in 22q13 Deletion Syndrome and SHANK3 Deficiency," *Molecular Autism*, vol. 4, pp. 1-17, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[12] Isabella R. Fernandes et al., "Genetic Variations on SETD5 underlying Autistic Conditions," *Developmental Neurobiology*, vol. 78, no. 5, pp. 500-518, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] Gary B. Mesibov, Victoria Shea, and Eric Schopler, *The TEACCH Approach to Autism Spectrum Disorders*, 1st ed., Springer New York, pp. 1-212, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[14] Nina Scarpinato et al., "Caring for the Child With an Autism Spectrum Disorder in the Acute Care Setting," *Journal for Specialists in Pediatric Nursing*, vol. 15, no. 3, pp. 244-254, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[15] Suman Raj, and Sarfaraz Masood, "Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques," *Procedia Computer Science*, vol. 167, pp. 994-1004, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Tania Akter et al., "Machine Learning-Based Models for Early Stage Detection of Autism Spectrum Disorders," *IEEE Access*, vol. 7, pp. 166509-166527, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] Ugur Erkan, and Dang N.H. Thanh, "Autism Spectrum Disorder Detection with Machine Learning Methods," *Current Psychiatry Research and Reviews Formerly: Current Psychiatry Reviews*, vol. 15, no. 4, pp. 297-308, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[18] Kayleigh K. Hyde et al., "Applications of Supervised Machine Learning in Autism Spectrum Disorder Research: A Review," *Review Journal of Autism and Developmental Disorders*, vol. 6, pp. 128-146, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[19] Fawaz Waselallah Alsaade, and Mohammed Saeed Alzahrani, "Classification and Detection of Autism Spectrum Disorder Based on Deep Learning Algorithms," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, pp. 1-11, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Mengyi Liao, Hengyao Duan, and Guangshuai Wang, "Application of Machine Learning Techniques to Detect the Children with Autism Spectrum Disorder," *Journal of Healthcare Engineering*, vol. 2022, no. 1, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Ibrahim Abdulrab Ahmed et al., "Eye Tracking-Based Diagnosis and Early Detection of Autism Spectrum Disorder Using Machine Learning and Deep Learning Techniques," *Electronics*, vol. 11, no. 4, pp. 1-27, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Miklos Kralik, Autism Spectrum Disorder Classification, 2020. [Online]. Available: https://www.kaggle.com/competitions/abide/data

[23] S.Gopal Krishna Patro, and Kishore Kumar Sahu, "Normalization: A Preprocessing Stage," *International Advanced Research Journal in Science, Engineering and Technology*, vol. 2, no. 3, pp. vol. 2, no. 3, pp. 2015. [CrossRef] [Google Scholar] [Publisher Link]

[24] José M. Jerez et al., "Missing Data Imputation Using Statistical and Machine Learning Methods in a Real Breast Cancer Problem," *Artificial Intelligence in Medicine*, vol. 50, no. 2, pp. 105-115, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[25] Yuanyuan Liu et al., "Flower Classification via Convolutional Neural Network," *IEEE International Conference on Functional-Structural Plant Growth Modeling, Simulation, Visualization and Applications (FSPMA)*, Qingdao, China, pp. 110-116, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[26] Giorgos Tolias, Ronan Sicre, and Hervé Jégou, "Particular Object Retrieval with Integral Max-Pooling of CNN Activations," *International Conference on Learning Representations*, pp. 1-12, 2016. [Google Scholar] [Publisher Link]

[27] Bernhard Scholkopf, Jean-Philippe Vert, and Koji Tsuda, *Kernel Methods in Computational Biology*, MIT Press, pp. 1-410, 2004. [Google Scholar] [Publisher Link]

[28] M. Pal, and P.M. Mather, "Support Vector Machines for Classification in Remote Sensing," *International Journal of Remote Sensing*, vol. 26, no. 5, pp. 1007-1011, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[29] Muhammad Shuaib Qureshi et al., "Prediction and Analysis of Autism Spectrum Disorder Using Machine Learning Techniques," *Journal of Healthcare Engineering*, vol. 2023, no. 1, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]