International Journal of Multidisciplinary Research and Growth Evaluation

International Journal of Multidisciplinary Research and Growth Evaluation
ISSN: 2582-7138
Received: 18-11-2020; Accepted: 20-12-2020
www.allmultidisciplinaryjournal.com
Volume 1; Issue 5; November-December 2020; Page No. 978-983

A Predictive Model for Early Diagnosis of Autism: Leveraging Machine Learning and Public Health Data

Salewa Gloria Akinse [1*], Ngozi Vivian Ekechi [2], Chiamaka Grace Ohanebo [3]
[1] Standard Atlantic Resources, Uyo, Nigeria
[2] Labhud Medical Diagnostic, Nigeria
[3] Independent Researcher, United States

Corresponding Author: **Salewa Gloria Akinse**

DOI: https://doi.org/10.54660/.IJMRGE.2020.1.5.978-983

Abstract
Early diagnosis of autism is critical for improving developmental outcomes through timely intervention. Traditional diagnostic practices often face challenges, including resource constraints, delayed recognition of symptoms, and variability in diagnostic accuracy across populations. This paper explores the development of a predictive model leveraging machine learning and public health data to address these limitations. The integration of advanced algorithms with large-scale datasets enables identifying at-risk children at earlier stages of development. The proposed framework incorporates key components such as risk stratification, personalized intervention planning, and resource allocation optimization. Ethical considerations, including data privacy and algorithmic bias, are thoroughly examined to ensure equitable outcomes and ethical deployment. By synthesizing findings from existing predictive models, advancements in healthcare technologies, and public health applications, this paper underscores the transformative potential of predictive tools in autism care. It concludes with recommendations for implementation, emphasizing the need for collaborative efforts between healthcare providers, technology developers, and policymakers to realize the full benefits of this approach.

Keywords: Autism diagnosis, predictive model, machine learning, public health data, early intervention, ethical considerations

1. Introduction
1.1. Overview of Autism and the Importance of Early Diagnosis
Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by challenges in social interaction, communication, and repetitive behaviors. The disorder affects individuals differently, with a broad range of severity and manifestations, making its diagnosis complex (Hirota & King, 2023). Early diagnosis is critical because it enables timely intervention, significantly improving developmental outcomes (Kamruzzaman, Islam, Siddique, Ahsan, & Azam, 2019). Research has demonstrated that early therapeutic interventions can enhance language skills, social interaction, and overall quality of life for individuals with ASD. Despite its prevalence, many cases go undiagnosed or are identified late, especially in low-resource settings. The global burden of ASD underscores the necessity for effective diagnostic tools to ensure no child is left behind in receiving appropriate care (Bertelli *et al*., 2022).

The significance of early detection cannot be overstated. Beyond individual benefits, early identification reduces long-term societal costs associated with delayed diagnosis, such as increased dependence on social support systems. Parents and caregivers are also better equipped to provide the necessary support when they receive an early diagnosis. Consequently, the development of innovative approaches to identifying ASD early is not only a clinical imperative but also a societal responsibility (Van Heijst & Geurts, 2015).

1.2. Challenges in Current Diagnostic Practices
Current diagnostic practices for ASD predominantly rely on clinical observations and standardized assessments performed by trained specialists. These practices, while effective in controlled settings, are time-consuming and resource-intensive (Hayes, Ford, Rafeeque, & Russell, 2018). A significant challenge lies in the global disparity in access to specialists, particularly in underserved or rural areas. This limitation results in delayed diagnoses and missed opportunities for early intervention.

Subjectivity in clinical assessments also poses a barrier to accurate diagnosis. Variations in cultural norms, parental reports, and observer biases can influence diagnostic outcomes. For instance, behaviors deemed atypical in one cultural context might be considered normal in another, complicating universal diagnostic standards. Additionally, comorbid conditions, such as ADHD or sensory processing disorders, further obscure the diagnostic process, as their symptoms may overlap with those of ASD(Zwaigenbaum & Penner, 2018).

Another pressing challenge is the underrepresentation of diverse populations in diagnostic research and practice. Diagnostic tools are often developed and validated within homogenous populations, limiting their generalizability to broader demographic groups. This bias exacerbates disparities in diagnosis and care, disproportionately affecting marginalized communities. Addressing these challenges necessitates innovative, scalable, and objective diagnostic methods that transcend limitations (Mukherjee, 2017).

1.3. Relevance of Machine Learning and Public Health Data

Machine learning (ML) has emerged as a transformative tool in the healthcare domain, offering unparalleled opportunities for innovation in ASD diagnosis. ML algorithms can identify subtle patterns and correlations that may elude traditional diagnostic methods by analyzing vast and complex datasets (do Rêgo & Araújo-Filho, 2024). In the context of ASD, ML models can process behavioral data, genetic markers, and neuroimaging results to generate predictive insights with high accuracy. This capability is particularly valuable in detecting early signs of ASD, which may be too subtle for conventional diagnostic techniques.

Public health data represents a rich resource for enhancing ASD diagnosis. Population-level datasets, including electronic health records, developmental screening results, and early childhood assessments, can provide valuable inputs for training ML models. By integrating such data, predictive models can account for demographic and socioeconomic variables, increasing their relevance across diverse populations. Furthermore, public health data facilitates large-scale analyses that can uncover previously unexplored trends and risk factors associated with ASD (Albert, Daniels, Schwartz, Du, & Wall, 2017).

The synergy between ML and public health data holds immense potential for transforming the diagnostic landscape. Unlike traditional methods, these technologies enable scalable and cost-effective solutions, making early diagnosis more accessible to underserved regions. For example, mobile health applications powered by ML can offer preliminary screening tools that are user-friendly and widely deployable. Such innovations empower caregivers and primary care providers to identify at-risk children, prompting timely referrals for further evaluation (Rasool, Husnain, Saeed, Gill, & Hussain, 2023).

In addition to improving accessibility, ML-driven approaches enhance the objectivity and consistency of ASD diagnosis. Algorithms trained on diverse datasets are less prone to the biases inherent in human assessments. They can also continuously evolve and improve as new data becomes available, ensuring that diagnostic practices remain up-to-date with the latest scientific advancements (Sravani & Pothanaicker, 2024). The integration of ML and public health data not only addresses existing diagnostic challenges but also paves the way for personalized care. Predictive models can identify individual risk profiles, enabling tailored interventions that align with the unique needs of each child. Such precision is vital for optimizing developmental outcomes and reducing the burden on healthcare systems.

In conclusion, the importance of early diagnosis in ASD cannot be overstated, given its profound implications for individuals, families, and society. Current diagnostic practices, while valuable, face significant challenges that limit their effectiveness and accessibility. The advent of ML and the utilization of public health data offer promising avenues for overcoming these barriers. Together, they represent a paradigm shift in ASD diagnosis, ushering in an era of innovation, inclusivity, and improved outcomes for all affected individuals.

2. Literature Review

2.1. Review of Existing Predictive Models for Autism Diagnosis

Over the years, several predictive models have been developed to aid in autism diagnosis. These models leverage various data sources, including behavioral assessments, genetic information, and neuroimaging data. Traditional predictive models often rely on rule-based systems derived from diagnostic criteria outlined in standard frameworks such as the DSM-5. These models have demonstrated utility in identifying core symptoms of autism, particularly in clinical settings (Prama, Islam, Anwar, & Jahan, 2024).

Behavioral-based models remain the most common and rely on observable indicators, such as language development and social interaction patterns. Tools like the Autism Diagnostic Observation Schedule (ADOS) and the Autism Diagnostic Interview-Revised (ADI-R) serve as gold standards in these models. However, their reliance on subjective interpretation and in-person administration limits scalability and accessibility, particularly in underserved regions (Drakeford & Majebi, 2024e; Kelvin-Agwu, Adelodun, Igwama, & Anyanwu, 2024b).

Genetic models have also shown promise, focusing on identifying genetic mutations and variations associated with autism. Advances in genome-wide association studies have highlighted specific risk genes, enabling researchers to develop predictive frameworks based on hereditary data. Despite their potential, these models are often constrained by limited sample sizes and high costs, which impede their integration into routine diagnostic practices (Tam *et al.*, 2019).

More recently, neuroimaging-based models have emerged as a sophisticated approach to autism diagnosis. Functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) provide insights into atypical neural activity patterns associated with autism. Although these models exhibit high accuracy, their reliance on expensive equipment and specialized expertise restricts their application to research settings.

The limitations of traditional predictive models underscore the need for innovative, scalable solutions. Emerging approaches that combine diverse data sources, such as behavioral, genetic, and neuroimaging data, into hybrid models have demonstrated improved diagnostic accuracy. These integrative frameworks set the stage for the next generation of predictive tools capable of addressing current challenges (Drakeford & Majebi, 2024d).

2.2. Role of Public Health Data in Early Detection

Public health data plays a pivotal role in advancing autism diagnosis, offering a wealth of information that extends beyond individual clinical settings. These datasets, which include electronic health records, developmental screening results, and school-based assessments, provide population-level insights into risk factors and prevalence trends. One of the key advantages of public health data is its ability to capture early developmental indicators, such as delays in speech and motor skills, on a large scale. Screening programs conducted during early childhood often generate extensive datasets that can be harnessed to identify autism-associated patterns. For example, longitudinal studies tracking developmental milestones over time have revealed critical windows for early diagnosis and intervention (Majebi, Drakeford, Adelodun, & Chinyere, 2023).

Additionally, public health data facilitates the identification of disparities in autism diagnosis across different demographic groups. By analyzing variables such as socioeconomic status, geographic location, and access to healthcare, researchers can pinpoint populations at higher risk of delayed diagnosis. This information is invaluable for designing targeted interventions and ensuring equitable access to diagnostic resources (Aylward, Gal-Szabo, & Taraman, 2021).

The integration of public health data into predictive models also enhances their generalizability. Unlike datasets from specialized clinical studies, public health data encompasses diverse populations, making predictive models more representative and robust. Furthermore, public health data enables real-time monitoring of diagnostic trends, allowing healthcare systems to adapt to emerging challenges and priorities (Luo, Wu, Gopukumar, & Zhao, 2016). However, leveraging public health data for autism diagnosis is not without challenges. Data privacy, standardization, and interoperability issues often hinder the seamless integration of these datasets into predictive frameworks. Addressing these challenges requires collaborative efforts between healthcare providers, policymakers, and technology developers to establish secure, standardized data-sharing protocols (Drakeford & Majebi, 2024b, 2024c).

2.3. Advances in Machine Learning Applications in Healthcare

Machine learning has revolutionized the healthcare landscape, offering innovative solutions to complex diagnostic challenges, including autism. Unlike traditional statistical methods, machine learning algorithms can analyze vast datasets, uncovering subtle patterns and correlations that may not be immediately apparent.

In autism diagnosis, machine learning has been applied to various data types, including behavioral, genetic, and neuroimaging data. For example, supervised learning algorithms trained on labeled datasets can classify individuals as at risk or not at risk based on specific diagnostic criteria. These models have demonstrated high accuracy in detecting early signs of autism, particularly when applied to behavioral data collected during early childhood (Hyde *et al*., 2019).

Unsupervised learning approaches have also shown promise in identifying subtypes of autism. By clustering individuals with similar behavioral or genetic profiles, these algorithms provide insights into the heterogeneity of autism, enabling more personalized diagnostic and intervention strategies. Reinforcement learning, another emerging area, has been used to develop interactive diagnostic tools that adapt based on user responses, enhancing their reliability and usability (Gardner-Hoag *et al*., 2021).

The use of machine learning in neuroimaging analysis has been particularly transformative. Algorithms trained on fMRI and EEG data can detect atypical neural connectivity patterns associated with autism, achieving diagnostic accuracies that rival expert clinicians. Similarly, machine learning has facilitated the development of speech and facial recognition tools that analyze communication and social interaction patterns, providing non-invasive diagnostic options (Du, Fu, & Calhoun, 2018).

Despite these advances, challenges remain in integrating machine learning into routine diagnostic practices. Issues such as algorithmic bias, data scarcity, and lack of interpretability can undermine the reliability of these models. Ensuring that machine learning models are trained on diverse and representative datasets mitigates these challenges. Moreover, efforts to enhance the explainability of algorithms can build trust among clinicians and caregivers, fostering greater adoption of these technologies (Adelodun & Anyanwu; Majebi, Adelodun, & Chinyere).

3. Proposed Predictive Framework

3.1. Key Components of the Predictive Model

A robust predictive model for the early diagnosis of autism should incorporate several critical components to ensure accuracy, scalability, and applicability across diverse populations. The first component is a comprehensive data collection mechanism. This involves gathering multidimensional data, including behavioral indicators, demographic information, genetic markers, and neuroimaging results. Such data provides a holistic view of potential risk factors, enabling the model to identify subtle patterns that may indicate early signs of autism.

The second component is feature engineering, which transforms raw data into meaningful inputs for the predictive algorithm. In this context, features might include developmental milestones, such as language acquisition, motor skills, and social interactions, as well as environmental factors like parental age and exposure to pollutants. Careful selection and preprocessing of features are essential to minimize noise and improve the model's predictive performance.

The third component is the predictive algorithm itself. Machine learning techniques, such as ensemble methods, neural networks, or gradient boosting, are well-suited for this purpose because they can handle large and complex datasets. These algorithms can be trained on labeled datasets to recognize patterns associated with autism, while unsupervised methods can uncover previously unknown subtypes or clusters of risk profiles.

Another vital component is the model evaluation and validation process. To ensure reliability, the predictive model must be tested on diverse datasets that reflect the heterogeneity of real-world populations. Metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve can assess the model's diagnostic accuracy. Cross-validation techniques further enhance robustness, reducing the risk of overfitting. Finally, the framework must include mechanisms for continuous learning and adaptation. As new data becomes available, the model should be capable of updating its parameters and refining its predictions. This dynamic approach ensures that the predictive tool remains current and effective as scientific knowledge and diagnostic practices evolve.

3.2. Integration of Public Health Data and Machine Learning Techniques

The integration of public health data with machine learning techniques forms the backbone of the proposed predictive framework. Public health datasets, which include electronic health records, developmental screening results, and population health surveys, provide a rich source of information for training and validating predictive models. By leveraging these datasets, the model can account for various factors, such as demographic diversity and social determinants of health, that influence autism diagnosis.

Machine learning techniques are pivotal in extracting actionable insights from public health data. Supervised learning algorithms can identify correlations between specific risk factors and autism diagnoses, while unsupervised methods can detect patterns or clusters that may not be immediately apparent. Reinforcement learning, on the other hand, can be used to optimize the decision-making process, such as determining the most effective screening protocols for different populations.

Data integration also enhances the scalability of the predictive framework. Combining machine learning with public health infrastructure allows the model to be deployed at scale, reaching underserved and remote regions. For instance, mobile applications powered by machine learning can analyze data collected during routine health checkups or community-based screenings, providing preliminary risk assessments that inform subsequent diagnostic evaluations (Udegbe, Nwankwo, Igwama, & Olaboye, 2023). Moreover, integrating public health data into the framework enables the identification of population-level trends and disparities in autism diagnosis. Such insights can guide policymakers and healthcare providers in designing targeted interventions, improving access to diagnostic resources, and addressing systemic inequities.

3.3. Benefits and Potential Applications

The proposed predictive framework offers numerous benefits and has the potential to revolutionize the early diagnosis of autism. One of the most significant advantages is improved diagnostic accuracy. By incorporating multidimensional data and leveraging advanced machine learning techniques, the model can detect subtle and early signs of autism that traditional methods may overlook.

Another key benefit is enhanced accessibility. The use of public health data and mobile health technologies enables the deployment of predictive tools in various settings, including primary care clinics, schools, and community centers. This approach reduces reliance on specialized diagnostic services, making early diagnosis more accessible to underserved populations.

The framework also supports personalized care by identifying individual risk profiles. This capability allows healthcare providers to tailor interventions based on the unique needs of each child, optimizing developmental outcomes and reducing the burden on families. For example, children identified as high-risk could be referred for intensive early intervention programs, while those with moderate risk might benefit from periodic monitoring and support.

In addition to clinical applications, the predictive model has broader implications for public health and research. Population-level analyses enabled by the framework can inform policy decisions, such as resource allocation and the design of early intervention programs. Furthermore, the data generated by the predictive model can contribute to scientific research, deepening our understanding of autism's underlying mechanisms and risk factors.

Ethical considerations are integral to the successful implementation of this framework. Ensuring data privacy, transparency, and fairness in machine learning algorithms is essential to building stakeholder trust. By addressing these concerns, the predictive model can foster greater acceptance and adoption, ultimately improving outcomes for individuals with autism and their families.

4. Implications and Ethical Considerations

4.1. Impact on Early Intervention Strategies

The introduction of a predictive model for the early diagnosis of autism carries profound implications for early intervention strategies. Early diagnosis is critical for optimizing developmental outcomes, as it enables timely access to interventions that target core challenges, such as social communication deficits and repetitive behaviors. By identifying at-risk children during critical developmental windows, the model supports more effective and tailored intervention plans (Kelvin-Agwu, Adelodun, Igwama, & Anyanwu, 2024a).

A predictive model powered by machine learning can refine the precision of early interventions. For example, it can stratify children into different risk categories based on their unique developmental profiles, allowing clinicians to prioritize resources for those who need intensive support. Such stratification ensures efficient allocation of intervention services, particularly in resource-constrained settings. Additionally, predictive tools integrated into primary care settings can serve as a first line of detection, facilitating referrals to specialized services.

The model also has the potential to revolutionize individualized education plans (IEPs) in school systems. Early identification enables schools to design specialized programs that cater to the specific needs of children with autism, promoting better academic and social outcomes. Furthermore, the insights generated by the model can inform caregiver training, equipping families with strategies to support their child's development at home.

Despite these advantages, the widespread adoption of predictive tools requires integration with existing intervention frameworks. Collaboration between healthcare providers, educators, and policymakers is essential to ensure that actionable and evidence-based interventions follow identified risks. Without such collaboration, the benefits of early diagnosis may not translate into meaningful improvements in developmental outcomes (Majebi, Adelodun, & Anyanwu, 2024b; Majebi *et al*., 2023).

4.2. Ethical Concerns Regarding Data Use and Bias in Algorithms

Predictive models raise significant ethical concerns, particularly regarding data use and algorithmic bias. Public health datasets often contain sensitive information, including medical histories, demographic details, and behavioral assessments. Ensuring the privacy and security of this data is paramount to gaining the trust of individuals and communities. Robust encryption methods, anonymization techniques, and compliance with legal frameworks like

HIPAA are essential for safeguarding data integrity.

Algorithmic bias represents another critical ethical challenge. Machine learning models are only as unbiased as the data they are trained on, and existing datasets may reflect systemic inequities, such as disparities in healthcare access or cultural differences in behavioral norms. For instance, a model trained predominantly on data from high-income populations may underperform in diagnosing autism among underserved groups. Such biases can exacerbate existing disparities, limiting the model's utility in achieving equitable outcomes.

To address these concerns, developers must prioritize transparency and accountability in model design and deployment. Regular audits of the model's performance across diverse demographic groups can identify and mitigate biases. Additionally, involving stakeholders, including clinicians, caregivers, and individuals with autism, in the model development process can ensure that ethical considerations are integrated from the outset.

Another ethical dimension involves the potential misuse of predictive data. For example, identifying children as high-risk for autism could inadvertently lead to stigmatization or discrimination, particularly in educational or social contexts. Clear guidelines on data sharing and usage are necessary to prevent such outcomes, ensuring that the predictive model is used solely to improve care and intervention strategies (Adelodun & Anyanwu, 2024b; Majebi, Adelodun, & Anyanwu, 2024a).

4.3. Broader Implications for Public Health Systems

Integrating predictive models into public health systems has far-reaching implications beyond autism diagnosis. These models can inform population-level strategies by leveraging public health data, enabling healthcare systems to allocate resources more effectively. For instance, predictive insights can guide the distribution of early intervention programs, ensuring that they reach underserved communities with the greatest need.

Predictive tools also enhance the capacity for public health surveillance. By monitoring trends in autism prevalence and risk factors, health authorities can identify emerging patterns and adjust policies accordingly. For example, if a specific geographic region exhibits a high incidence of developmental delays, targeted outreach and screening initiatives can be implemented to address the underlying factors (Drakeford & Majebi, 2024a; Oshodi, Adelodun, Anyanwu, & Majebi, 2024).

Predictive models can also streamline healthcare delivery by reducing the burden on specialized diagnostic services. As these tools become integrated into primary care workflows, they enable earlier detection and referral, alleviating bottlenecks in specialized clinics. This approach improves access to care and reduces the costs associated with delayed diagnosis and treatment. However, adopting predictive models requires careful consideration of infrastructure and workforce readiness. Public health systems must invest in training healthcare providers to use these tools effectively and interpret their results accurately. Additionally, ensuring interoperability between predictive models and existing health information systems is critical for seamless integration and data sharing.

From a policy perspective, the success of predictive models depends on a supportive regulatory environment. Policymakers must establish guidelines for the ethical use of machine learning in public health, addressing concerns such as data ownership, algorithm transparency, and accountability for outcomes. Public health systems can maximize the benefits of predictive tools while mitigating potential risks by fostering a collaborative environment between technology developers, healthcare providers, and policymakers (Adelodun & Anyanwu, 2024a; Majebi, Adelodun, & Chinyere).

4.4. Conclusion and Recommendations

Developing and implementing a predictive model for the early diagnosis of autism represent a transformative approach to addressing the challenges associated with traditional diagnostic practices. Integrated with public health data, machine learning offers the potential to identify at-risk children with greater accuracy and at earlier stages of development. The review of existing predictive models highlights their ability to process complex, multidimensional data, including behavioral, genetic, and environmental factors, to generate actionable insights.

Public health data is crucial in enhancing the model's applicability and scalability, bridging gaps in diagnostic resources across diverse populations. Advances in machine learning techniques further strengthen the model's diagnostic capabilities, enabling precise risk stratification and personalized intervention planning. However, ethical concerns, such as data privacy and algorithmic bias, must be carefully addressed to ensure equitable outcomes and widespread acceptance.

The successful implementation of the proposed predictive model requires a multi-pronged approach. First, healthcare systems must invest in infrastructure to support the collection, storage, and analysis of high-quality data. Ensuring interoperability between predictive models and existing health information systems is critical for seamless integration. Moreover, healthcare providers should receive training on the interpretation and application of predictive outputs to inform clinical decisions. Second, rigorous evaluation of the predictive model across diverse populations is necessary to identify and mitigate potential biases. Continuous monitoring and refinement of algorithms will enhance their performance and ensure that they remain relevant as new data becomes available. Developers should also prioritize transparency in model design, providing clear documentation of data sources, methodologies, and validation processes.

Future research should explore the potential of combining machine learning with emerging technologies, such as natural language processing and wearable devices, to expand the scope of predictive tools. Additionally, longitudinal studies are needed to assess the long-term impact of early diagnosis and intervention on developmental outcomes. Exploring the cost-effectiveness of predictive models in various settings can further inform policy decisions and funding allocations.

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