Machine Learning-Based Clinical Decision Support Systems in Dementia Care

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Keywords: Dementia, Clinical Decision Support Systems, Deep Learning, Caregiver Support.

Abstract: Clinical Decision Support Systems (CDSSs) enabled by machine learning (ML), particularly those based on deep learning (DL), are revolutionizing dementia care by offering advanced capabilities that go beyond the capacities of manual CDSSs, rule-based CDSSs, and statistical CDSSs. This paper explores unique applications of ML in dementia care. It focuses on areas where ML-based, especially DL-based (neural network-based) CDSSs currently excel and can potentially be of relevance. Unlike conventional CDSSs, which evidently struggle with the complexities of large, heterogeneous datasets, ML models, particularly DL-based ones, are capable of better identifying hidden patterns and subtle relationships across diverse genetic and multi-omic, clinical, behavioural, socioeconomical and cultural, and environmental data. These systems also extend their utility beyond clinical decision-making and caregiver wellbeing through tailored support recommendations and aiding hospital administrators in resource mobilization, staff augmentation, and policy formulation. However, challenges such as model interpretability, extensive data requirements, and infrastructure limitations must be addressed. This article highlights the importance of a collaborative approach, where various stakeholders in dementia come together to pool data and recommendations that would assist in inculcating comprehensiveness and inclusivity in future CDSSs. We hypothesize that as DL continues to showcase its decided prowess in the arena of decision-making, its applications in CDSSs will keep playing an exceedingly pivotal role in advancing the efficacy of dementia care, improving patient outcomes, and shaping the future of healthcare.

SCIENCE AND TECHNOLOGY PUBLICATIONS

1 INTRODUCTION

In healthcare and medicine, decision support is crucial for a variety of stakeholders, each of whom can utilize customized assistance to eventually benefit those who receive care. Decision support helps the stakeholders optimize care delivery and patient outcomes. Such stakeholders are many, but the primary ones are healthcare providers and policymakers, whose verdicts can have a momentous bearing on those who are on the receiving end of the impact of their decisions. The chief people involved in enriching their decisions with evidence are data collectors, as well as researchers and analysts. The entire pipeline or the process of collecting data, quarrying and assembling trends, patterns and insights from it, and using these analytics to inform decision making is encapsulated in what is called a decision support system (DSS).

DSSs are information-powered systems relying on statistical and factual data to process it into actionable knowledge, which is often in the form of visualized data (a comprehensible, interest-piquing format), and which fuels rational decision-making. Although principally DSSs involve computational components, there can be DSSs which do not involve any computer-based tools or design. The idea of DSS was conceptualized in 1960s (Keen & Morton, 1978). When applied to clinical settings, DSSs are termed Clinical Decision Support Systems (CDSSs), and their major function here is aiding decision-makers in medical diagnostics. CDSSs evolved through four stages, standalone CDSSs, integrated systems, standards-based systems, and service models which (Wright & Sittig, 2008).

CDSSs can be typified on multiple bases. The first basis is their function, or rather their style of function.

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Saxena, R. R. and Khan, A.
Machine Learning-Based Clinical Decision Support Systems in Dementia Care.
DOI: 10.5220/0013194100003911
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 2: HEALTHINF*, pages 664-671
ISBN: 978-989-758-731-3; ISSN: 2184-4305
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Some answer the question “what to choose”, while others tell users “what to do.” Active and passive CDSSs are other clades of CDSSs. Passive ones act on a user-provided cue, while active ones provide automated alerts and act on their own (Wasylewicz & Scheepers-Hoeks, 2018).

While CDSSs that are completely manual are not only possible to be but also to have existed, when thinking about CDSSs currently, it is impossible to find a person who would describe CDSSs without an implication that these systems are run on, dependent on, or directly associated with computers and are computational tools. CDSSs are manifestations of evidence-based medicine and therefore, rely on statistical data and its analysis to serve as evidence for its suggestions. The strongest tool presently available in the realm of analysing data and drawing the most meaningful insights from it is ML. A key area of AI, ML automates detection, classification, prediction, and generative tasks with high efficacy.

CDSSs can have a variety of applications in medicine and healthcare. During the prescription and medication process, the presence of CDSSs ensures default values for drug doses and frequencies and advise about patient-specific drug allergies and adverse drug interactions. By reducing manual transcription errors and ordering, a computerized provider order entry (CPOE) system enhanced with a CDSS mitigates treatment-associated expenditures. CDSSs can reduce dosing errors by 55% and improve adherence to evidence-based protocols (Kuperman et al., 2007; Saxena & Saxena, 2024). CDSSs considerably enhance diagnostic accuracy. It offers symptom-specific guidance and provides auto-analysis of complex patient data, including medical history, test results, and risk factors (Sutton et al., 2020), evidence-based recommendations, and real-time support (Zhao et al., 2023). Chronic conditions such as cancer, chronic obstructive pulmonary disease, and dementia require continuous monitoring and evidence-based management, thereby benefiting from use of CDSSs (Gencturk et al., 2024).

CDSSs improve healthcare delivery at population level by tracking key performance indicators (KPIs) and inspiring adherence to clinical guidelines. CDSS-powered predictive analytics enables outcome prediction (such as the likelihood of hospital re-admission, disease progression) and mortality and risk stratification of patients, prioritizing interventions for those at higher risk (Snooks et al., 2018). Natural language processing (NLP) enables CDSSs to extract meaningful insights by analysing unstructured data, such as clinical notes, patient histories, and medical literature (Berge et al., 2023). CDSSs power personalized medicine by tailoring treatment and intervention recommendations to individual patients based on their genetic and multi-omic profile, environmental factors, personal and familial history, and lifestyle (Zhao et al., 2023).

CDSSs enable successful drug repurposing, where new therapeutic uses for existing drugs are identified (Zong et al., 2022). CDSSs also facilitate real-time remote patient monitoring through integration with telehealth services via linkages with wearable devices, smart health apps, and home monitoring. A CDSS can directly interact with patients online (telemedicine) to provide virtual consultation in the form of a text- or speech-based intelligent conversation agent (Jadczyk et al., 2021), ensuring patient empowerment.

CDSSs are applicable in toxicology management by predicting patient poisoning and identifying its cause of poisoning (Badcock, 2000). They assist in the design and analysis of clinical trials (Embi et al., 2009). For holistic care, CDSSs integrate herbal and alternative therapies into its treatment recommendations. CDSSs enable patient engagement and patient confidence-building by providing patients with personalized information and education about their health conditions through patient portals, and empowering them to access their health records, to schedule appointments, and to communicate with their healthcare providers (Dendere et al., 2019; Hägglund et al., 2022).

Shared decision-making models, which use CDSSs to present options based on patient-specific data, improve patient satisfaction and adherence to patient-opted treatment plans (Zhao et al., 2023; Breitbart et al., 2020). The use of decision aids in patient-centred care increases patient knowledge and lowers decisional conflict (Alden et al., 2013). CDSSs help hospital administrators by causing improvement in operational efficiency through better resource planning advice and more value-added healthcare regulation adherence recommendations. By using CDSSs, hospitals extenuate chances of medical errors, whereby they save on litigative costs. By avoiding unnecessary and duplicate tests and medications as decision proxies, CDSSs save clinical time and improve medicinal efficiency, through which they diminish patient costs as well as clinical costs (White et al., 2023).

2 APPLICATIONS OF CDSSs IN DEMENTIA CARE

CDSSs offer several applications that cater specifically to the challenges posed by dementia, which forms a class of neurodegenerative diseases characterized by cognitive and motor decline and include Alzheimer's disease as well as Lewy Body dementia (Bruun et al., 2019). Early detection of dementia helps slow down the progression of the ultimately mortal disease (Rasmussen & Langerman, 2019). CDSSs analyse data such as neuroimaging, genomic and multi-omic data and genetic markers, individual symptoms, health status, past conditions, as well as family history of a suspected person with dementia (PwD), their cognitive test results, and pathological test results, if relevant, to identify dementia as well as prodromal dementia (Kleiman et al., 2022; Karimi et al., 2020; Saxena et al., 2023; Johnson et al., 2020) long before noticeable symptoms arise. Timely intervention greatly enhances the quality of life for patients and can arrest the acceleration of evolution of dementia.

CDSSs engender personalized cognitive care planning in dementia care. CDSSs assess cognitive decline trajectory of PwDs and recommend tailored interventions, inter alia, memory exercises, serious games, lifestyle changes including physical exercise and dietary changes, pharmacological and physiotherapeutic treatments based on the individual's history, stage of dementia, mobility status, and progression patterns (Dietlein et al., 2018). A paradigm of personalized care is immensely applicable to dementia because in this disease, gender-, population-, age-, region- and patient-level specificity is observed not only with regards to symptomatology but also with regards to the pattern and speed of progression.

No two PwDs can be, with arrant certainty, said to display the same behaviour (behavioural variability) given the similarity in their ages, stage of dementia, level of cognitive decline, gender identicality and overlap of other factors. Genetic markers, individual medical and psycho-emotional history, environment, socio-familial dynamics and other factors influence the behaviour of a PwD (Cerejeira et al., 2012). CDSSs assist in management of behavioural, social, and psychological symptoms like agitation, aggression, depression and hopelessness, suicidality, misanthropy, anxiety, cynicism, and other similar issues in PwDs, specifically those in advanced stages of dementia (Müller-Spahn, 2003), in identifying triggers and recommending treatments.

Caregiver support directly influences and augments patient care. CDSSs play a critical role in it. Caring for PwDs is emotionally and physically taxing for their caregivers, whether the caregivers are hired or are informal caregivers (Lin et al., 2023). CDSSs provide caregivers with real-time guidance on managing challenging behaviours, alert them to critical changes in the PwD's condition, and offer widely applicable educational resources linked to dementia and other health conditions as well as those resources which are tailored to a PwD's specific stage of dementia. CDSSs also enable a caregiver to relay real-time alerts and warnings to healthcare professionals in case their ward, faces a medical emergency (Ponnala et al., 2020).

Caregivers, both formal and informal, are key users of CDSSs, which are their vital aides. CDSSs provide them with behaviour management tools and educational aids that provide guidance on handling the emotional and behavioural symptoms of their wards, as well as other pointers about suitable caregiving (Duplantier & Williamson, 2023; Antelo Ameijeiras & Espinosa, 2023). CDSSs also link them to resources which can uplift them when they feel overwhelmed by their duties or by perceived role captivity. CDSSs provide caregivers with resources on disease progression, care techniques, and strategies for managing activities of daily living (ADLs). For caregivers in general, and particularly for family (informal) caregivers, who juggle other responsibilities, CDSSs act as digital assistants who remind them about their wards' appointments and medication and care schedules.

Longitudinal tracking of cognitive decline is a significant feature of CDSSs in dementia (Rebok et al., 1990). CDSSs, using sensor data, IoT, and caregiver inputs, monitor changes in cognitive function of PwDs over time. CDSSs suggest reassessment in interventions as needed.

CDSSs in dementia care are integrated with network-enabled assistive technologies (Internet of Things or IoT), such as wearable devices like smartwatches, smartphones, intelligent exoskeletons (for those dementia patients with mobility impairments) and posture and balance assessment devices, home monitoring systems in smart homes, car dashboard assistants (for patient), virtual reality devices, hearing devices and aids, and so on, to gather data, inform healthcare providers and caregivers of real-time updates about PwDs' condition, and to support the patients in routine tasks and ADLs. These systems monitor vital signs, detect falls, and even assess whether a patient is adhering to prescribed daily routines. This underpins continuous and unobtrusive tracking of patients' symptoms and information connected to their adherence to treatment plans.

For physicians, nurses, and allied healthcare professionals engaged in treating PwDs, CDSSs assist in diagnosis, personalized treatment planning, and medication management (for example, for dementia patients who take multiple medications for comorbid conditions), real-time clinical guidance, identifying trends in patient incidents (e.g., falls, medication errors), implementing preventive measures to improve patient safety, and protocols for managing behaviour in PwDs (Lindgren, 2011). CDSSs improve operational efficiency and patient flow, optimize resource allocation (by demonstrating accuracy in predicting patient needs) and staffing requirements in dementia care units in hospitals (Chen et al., 2023).

For administrative purposes, CDSSs provide quality assurance services such as tracking clinical outcomes, clinical compliance with dementia care guidelines, and collecting data and providing insights by processing it and allowing its analysis to be used for internal audits, accreditation processes, and quality improvement initiatives. Dementia care unit managers use CDSSs for eliciting actionable recommendations for organizational risk management.

For clinical investigators engaged in researching dementia, CDSSs facilitate data collection and analysis for ongoing studies. These systems are fed large volumes of data from sources like electronic health records (EHRs), conversation logs between dementia stakeholders, particularly those between PwDs and their caregivers or their healthcare providers, clinical notes, patient reports, and caregiver feedback. The analytics provided by CDSSs based on such data empowers researchers to explore new hypotheses about dementia's pathology, aetiology, progression, treatment and so on. CDSSs help identify balanced patient cohorts (by applying probability distributions and sampling techniques to select highly representative groups as functional samples) for clinical trials based on specific biomarkers, symptoms, age, stage of disease, and so on (Kwan et al., 2020). CDSSs perform predictive analytics on dementia statistics and model dementia patterns under varied intervention and socio-environmental scenarios. This helps CDSSs discern trends that are not apparent via manual analysis (Gomez-Cabello et al., 2024).

Technologists and computer scientists are involved in building and refining software that powers CDSSs. They use the outcomes that researchers generate, the analytics that CDSSs generate, and the recommendations that other stakeholders in dementia care (SDCs) tender to inform their requirement gathering efforts for improving extant CDSSs and creating new and better ones (Elhaddad & Hamam, 2024).

3 MACHINE LEARNING-BASED CLINICAL DECISION SUPPORT SYSTEMS IN DEMENTIA CARE

The current applications of AI-based or ML-based CDSSs in dementia care are, straightforwardly or with some level of indirectness, prodigiously concentrated in the area of disease diagnostics in patients, that is, determination, prediction, detection, classification, recognition, or identification of, as the case may be, the presence of dementia or cognitive decline in a person, including mild cognitive decline as being prodromal to dementia or not, and the severity or the stage of dementia or cognitive decline as evident in a PwD (Rhodius-Meester et al., 2018). Automating diagnostics is a complex task which requires optimization of a multivariate setup, which involves numerous categorical and numerical variables. Therefore, while some of the other decision support tasks applicable to dementia care can be tolerably and, sometimes, quite capably performed though other techniques, diagnostics is best accomplished using DL methods, particularly because DL models can handle the non-linear relationships inherent in this task (Javeed et al., 2023).

DL models analyze enormous datasets and learn relevant features from raw data on their own. Their latter capability remedies the need for deriving features from the data manually or statistically. This is remarkably useful in domains such as dementia care where data is commonly dense and high-dimensional. DL models have demonstrated state-of-the-art performance on a variety of tasks, inter alia, medical image analysis, NLP (implementation of intelligent conversation agents in dementia care and so on) and predictive modeling (Karako et al., 2023). This makes them well-suited for determining diagnosis and prognosis in dementia care.

Techniques have been developed so that DL models can be expeditiously and unobtrusively integrated with other existing components of a CDSS, such as patient information systems (Maleki Varnosfaderani & Forouzanfar, 2024). While it is also indubitably true that diagnostics, being the principal manifestation of predictive analysis in medicine, and predictive analysis being the mainstay of ML – specifically DL – must be the primary use case of ML in a CDSS, there are multiple other uses that DL can perform when amalgamated in a CDSS.

One application of DL-enabled CDSSs in dementia care is predicting the incidence of dementia in a population based on large-scale datasets, including genetic makeup of the population, regional and environmental factors affecting the population, lifestyle and cultural-anthropological characteristics of the population, and historical dementia data for the population (Kim & Lim, 2021). This can be done in conjunction with studying how the incidence of dementia in that population evolved over time predicting, using DL, future trends of dementia incidence in that population. This helps with better resource allocation for the future dementia care for that population, educating the population about dementia and how to prevent it from affecting or delaying when it is inevitable, and implementing interceptive strategies that can prolong the onset and potentially reduce the incidence of dementia in the population.

Another critical application of DL is the analysis of a mishmash of unstructured data (which not only dementia, but also other domains of medicine are replete with), including heterogenous and multimodal data, first detecting where each piece of the disparate data fits (assigning labels to it using unsupervised learning) and then using those labels to extract features from it, visualize it and make predictions and extrapolations based on it (Taye, 2023). This requires not only the NLP capability of ML but also its competence in processing large quantities of multimodal data.

DL is more adept at drug repurposing than statistical CDSSs struggle. This is because DL-based CDSSs can mine or are fed with humongous (at times, almost exhaustive) amounts of drug-drug interaction and molecular reaction data, which is commonly an instance of high-dimensional data. Also, drug discovery and drug-drug interactions are modeled far more accurately by using DL than with statistical CDSSs (Chen et al., 2024). This integrates data from pharmacogenomics, multi-omics, clinical trial outcomes, and patient histories, and helps prevent adverse drug reactions and the possible occurrence of toxicity in patients. ML enables personalized drug therapy by considering individual patient data, such as genetic profiles and disease progression patterns. DL models can continuously analyze complex datasets. They can provide personalized predictions that adapt as new data becomes available, such as changes in patient cognition and behavior (Arya et al., 2023).

DL provides substantial benefits in decision-making processes in areas of dementia where non-linear data patterns need to be analyzed. While statistical techniques display the ability to determine the best intervention, including drugs and treatment plans, in individual cases of dementia, this task is performed far more accurately with DL models, which they accomplish by analyzing astronomical amounts of patient-specific data, including medical history, genetic information, and real-time health monitoring. Unlike traditional methods, DL identifies subtler patterns in disease progression data compared to statistical tools and suggests highly personalized treatments (Alowais et al., 2023).

DL techniques also exhibit much better promise in predicting the most appropriate approach to caregiver wellbeing by analyzing psychological and physical health data from caregivers. DL also informs and enhances the design of the best administrative policies in dementia care at the policy formulation echelons, reducing staff burnout by optimizing shifts, schedules, and employee numbers, concomitant with dementia incidence. DL-based CDSSs personalize cognitive exercises like serious games with unparalleled precision (Maggio et al., 2023).

4 DISCUSSION AND CHALLENGES

Implementing DL models, for CDSSs, presents various challenges. The complexity and interpretability of these models is a concern. Large Language Models (LLMs) are NLP models which are especially massive, and their inner workings are hard to decipher.

DL algorithms are often described as “black box” models due to the difficulty in understanding how they arrive at certain decisions (Hassija et al., 2023). In healthcare, where trust in technology is paramount, the inability to explain a model's predictions hinders its adoption (Rudin, 2019; Abgrall et al., 2024). To combat this, explainable AI (XAI) techniques like LIME and SHAP can be applied.

Another major challenge is the extensive training time required by DL models to achieve satisfactory performance metrics such as accuracy, precision, and F1 score. These models often require substantial computational power and vast amounts of data to reach optimal results. In dementia care, relevant clinical data might be scattered across multiple institutions and databases. Without sufficient data, training DL models becomes less feasible.

The deployment and integration of DL-based CDSSs come with infrastructural challenges. Smaller healthcare facilities do not have the necessary infrastructure to host DL models locally (Miotto et al., 2018). Cloud-based solutions offer scalability in such scenarios. However, they introduce concerns about data privacy, security, and cost (Mehrtak et al., 2021). They need regular updates and maintenance. This is burdensome for underfunded healthcare systems. Thus, infrastructural and technological investments are crucial.

Healthcare providers in dementia care should contribute data to a unified database. Extant repositories like Alzheimer's Disease Neuroimaging Initiative (ADNI) (Weiner et al., 2013) must be linked to form a centralized registry. Healthcare providers continuously generate new data. Insights from this data could be incorporated into the CDSSs.

One approach for reducing the training and running time of ML models is to ensure that the data contributed to CDSSs is properly structured and encoded so that ML models can interpret it effectively. Structured data can be easily converted into knowledge graph embeddings, which represent complex relationships between different data points, such as linking sociocultural information to clinical symptoms and treatment outcomes. These embeddings enable the ML models to process and learn from the data more efficiently.

5 FUTURE DIRECTIONS AND CONCLUSION

Our paper showcases that use of ML, particularly DL, as the underlying force that fuels CDSSs in dementia care can indeed serve significant improvements in their ability to accrue benefits to PwDs, to other SDCs, and to dementia care institutions, and incentivize computer scientists and technologists in this field. From early detection and diagnosis to personalized treatment planning and monitoring, DL-powered CDSSs have the potential to vastly improve outcomes for patients with dementia and reduce the burden on the healthcare provision and policymaking superstructure. While challenges exist, they can be overcome with conscientious research and development efforts and technological improvements. As research and development in this area continue to advance, we can expect to see even more innovative and impactful applications of DL in dementia care. Collaboration between various SDCs, while laying a particular emphasis on the involvement of PwDs, researchers, experts, and technologists, can help gather specific stakeholder needs, allowing for the design and development of inclusive CDSSs based on those needs. By working together with different SDCs, we can access a wider range of perspectives and details, leading to a more comprehensive understanding of the necessary information. Ensuring data privacy will remain key to the success of CDSSs.

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