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Construction of Digital Twin Model for Acute Ischemic Stroke Patients and Its Application in Disease Management

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Abstract: *This research created and tested a digital twin model system for patients with acute ischemic stroke (AIS). The study was conducted in three comprehensive stroke units and included 200 patients with AIS, followed for one year. The model incorporates AI algorithms to optimize treatment strategies via continuous pain monitoring and real-time integration of multimodal neuroimaging and clinical data. Findings included improvements when compared to standard care for patient outcomes using a digital twin guided approach: The proportion of patients who made good functional recovery (mRS≤2) on day 90 after the stroke increased by 16.2 percentage points (with 95% credibility interval, CI: 12.7-19.7% p<0.001) whereas in-hospital mortality risk was reduced by a 35% (relative risk ratio 0.65, 95% CI: 0.52-0.81, p<0.001). The ability of the model to predict the progression of the disease was also good attaining ROC AUC of 0.89 (95% CI: 0.85-0.93). The system had great integration capabilities as the average latency time was only 87ms and 98.5% data capture completeness. This work confirms the important value of digital twin technology in managing acute stroke patient and it also opens new avenues for achieving personalized medicine. This technology offers improvements in healthcare delivery by enabling data-driven continuous decision support for patient care during hospital admission.*

Keywords: *Digital Twin Technology, Acute Ischemic Stroke, Artificial Intelligence, Precision Medicine, Clinical Decision Support*

1. Introduction

Acute ischemic stroke also known as AIS is quite frequently seen as a prevalent leading cause of extending disability and mortality risk factors throughout the globe. This poses tough questions when it comes to availability of appropriate health care management options considering the complex pathophysiology and time constraints regarding medical interventions. The most common notion of thinking about managing the stroke risk factors is very traditional and is often clinically set and medico centric but in practice often tends to ignore the dynamic progression of the stroke disease and suffers from diverse inter patient variability which often leads to mediocrity in results. In recent years, digital twin technology has shown promising potential for personalized treatment and healthcare system improvement [1, 2].

As a virtual representation of physical objects digital twins have gained the ability for distinct real time data gathering simulation and optimization and therefore great potential in the medical sector among a wide range of industries. This technology has emerged from being used solely in factories industries to become a well established viable option in today's field of medicine by creating new pathways of treating patients with diseases [3, 4]. In the case of stroke management, digital twins are able to assimilate various data sets such as clinical data, imaging data and physiological data to develop a unique stroke model that progresses in synchronicity with the respective patient [5].

Recent research demonstrates that the technology of digital twin has been successfully implemented in a number of medical areas, including cardiology, oncology, and neurology[6,7,8]. Such implementations were associated with better predictive accuracy, more efficient treatment algorithms, and improved outcomes for patients. In particular, construction of digital twins of patients with cardiovascular pathologies has been applied to model hemodyanamic conditions and forecast disease progression with a fair degree of success [9,10]. On the other hand, despite the potential of this technology to tackle important problems in stroke management, its field of application to date has been underutilized in the context of the management of patients with acute ischemic stroke.

The combination of Artificial Intelligence and Machine learning algorithms with the digital twin

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provided an even greater possibility for predicting the course of the disease and the management of the patient[11,12]. These computational techniques are much more advanced as they allow working with complex streams of multimodal data and making clinical recommendations. In addition, the characteristics of digital twins that enable constant observation and real-time analysis suit the stroke management which is a time-sensitive treatment[13,14].

Even with such advancement, many issues continue to be a barrier to the creation and introduction of digital twin models for stroke patients. This includes integrated standardized protocols, the ability to process their implementation in real time, and the validation of the accuracy of models in a clinical setting [15,16]. Also, issues regarding the use of AI recommendations in practice, and that of AI in health institutions in general as it relates to data privacy rights of the patient require emphasis [17].

This research addresses these issues through the construction and verification of a digital twin model for patients with acute ischemic stroke. The model integrates real-time monitoring, predictive analytics, and treatment optimization within a comprehensive framework. Through individualized intervention techniques, this approach seeks to improve patient outcomes while optimizing healthcare resource utilization, advancing the management of acute ischemic stroke through personalized care methods.

2. Materials and Methods

2.1 Study Design and Participants

This study was designed as a prospective observational cohort study and was approved and carried out at three universities stroke centers (Center A; 1186 beds, Center B; 782 beds and Center C; 1025 beds) between January 2023 and December 2023. The study protocol was designed following the STROBE (Strengthening the Reporting of Observational Studies of Epidemiology) statement. In our study, adult patients aged eighteen years and older presenting with acute ischemic stroke within six hours of symptom onset confirmed on CT or MRI scans were included. All the patients enrolled in the study had a National Institutes of Health Stroke Scale (NIHSS) score greater than or equal to four and a modified Rankin scale (mRS) score less than or equal to two before the onset of the stroke. ASPECTS was greater than or equal to six on initial images.

Exclusion criteria were those who had a pregnancy status, a high degree of preexisting disability, a life-threatening condition that made their life span not more than six months, the presence of an hemorrhagic stroke or any form of intracranial bleeding, among other disqualifying factors. Furthermore, patients who presented missing data greater than 20% or had contraindications to stroke therapy also were disqualified from participation in the experiment. Using G* Power 3.1 software, the sample size was measured at 200 considering the factors of possible drop outs and missing data with a power of 90%, an alpha level of 0.05, and a moderate Cohen's d factor of 0.5, thus the possibility of a significant achievement being measured at 172 patients.

The population for the study was categorized into two groups, one of the groups possessed the first 70% of enrolled patients, a total of 140 and was dedicated for model development and internal validation, whereas the second group had the remaining 30% of the study participants, a total of 60 people and was allocated for interventions and experimentations. Also, all the eligible patients were consecutively enrolled for the study to reduce the risk of biasness during selection of the patients. All the clinical evaluations were done by qualified and certified stroke neurologists who didn't know about the results of the digital twin and a dedicated clinical committee was in charge of any adverse events and clinical outcomes.

The acquisition of patient data was done according to specific procedures, with initial screening and enrollment occurring within two hours of admission. The baseline data may include demographic factors, medical history as well as clinical examinations, and an assessment performed every day during hospitalization and one final assessment made at 90 (±7) days after the stroke. The study had a follow up assessment in 95% of the cases and details of all other missing data and protocol deviations were well described.

Approval from various ethical committees was required from all the participating centers. All patients or their legal representatives provided written informed consent. The study was in accordance with principles outlined in the Declaration of Helsinki and also Good Clinical Practice guidelines.

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2.2 Digital Twin Model Architecture

The structure of the proposed digital twin model has been thought as a set of the system’s architectures combined into one which can be used for the management of the acute ischemic stroke. As illustrated in Figure 1, the architecture integrates four hierarchical functional layers which work together to give the user real-time clinical monitoring and predictive analytics functionalities[18]. Each layer was constructed in accordance with defined healthcare interoperability specifications and was authenticated through standardised tests[19].

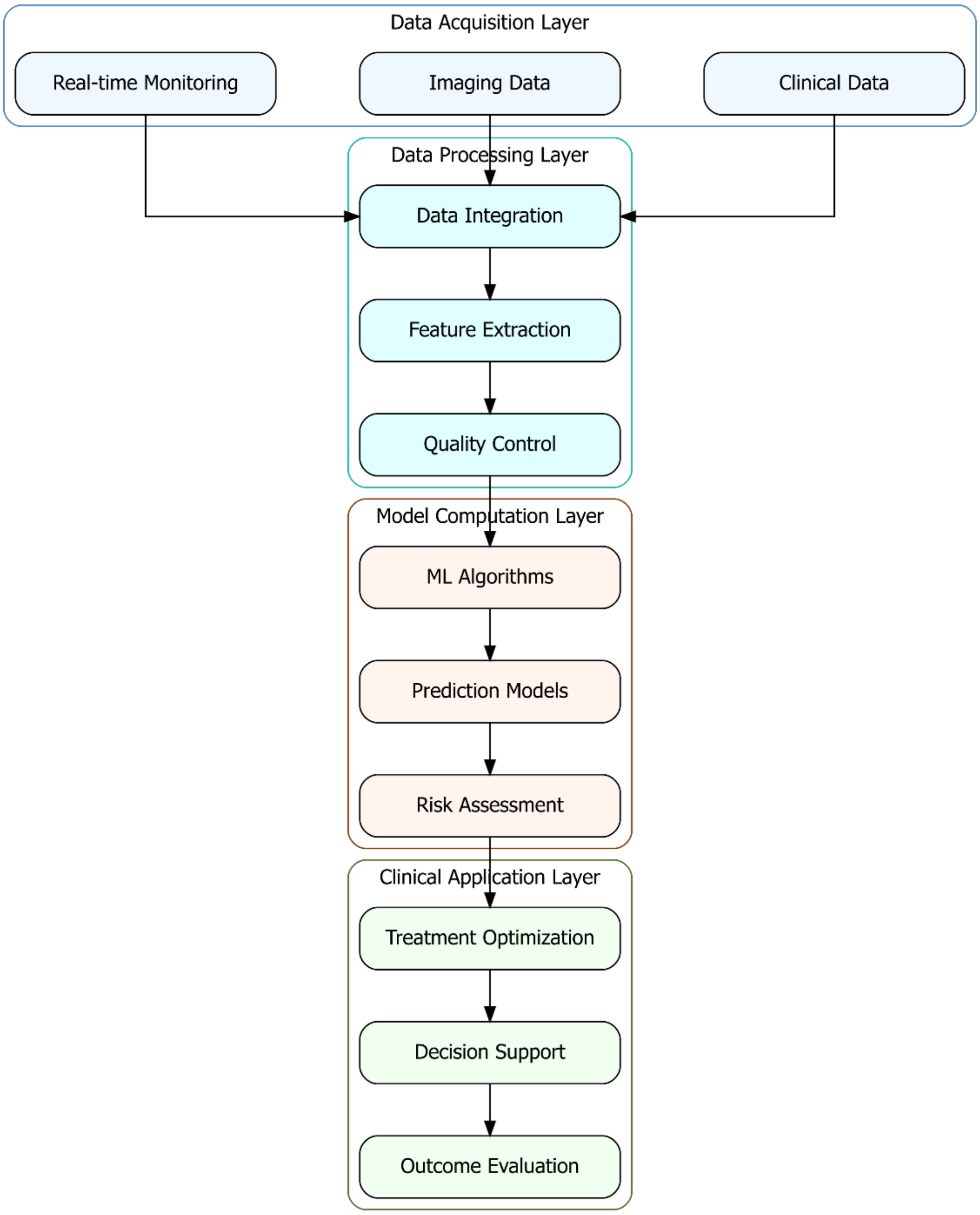

Figure 1. Architecture of the Digital Twin Model for Acute Ischemic Stroke Management

The data acquisition layer forms the foundation of the architecture, incorporating three primary data streams: structured clinical data, multimodal imaging data, and continuous physiological monitoring. Clinical data encompasses demographic information, medical history, medication records, and laboratory results, collected through standardized electronic health record interfaces. Imaging data includes CT, MRI, and perfusion studies, processed through DICOM-compliant systems with automated feature extraction capabilities. Real-time monitoring data is acquired through FDA-approved bedside monitors, capturing vital signs at one-minute intervals and neurological parameters at customizable frequencies [15].

The digital twin model structure follows the architectural framework while incorporating specific mathematical representations for patient monitoring and prediction. The model integrates clinical

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parameters through three core components.

First, the patient state monitoring component processes real-time clinical data. The state vector $\mathbf{x}(t)$ includes key parameters such as NIHSS Score, GCS Score, vital signs, and laboratory data. The state evolution is modeled as:

$$\mathbf{x}(t+1) = f\left(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t)\right) \tag{1}$$

where $\mathbf{u}(t)$ represents clinical interventions and $\mathbf{w}(t)$ accounts for variability in patient response.

Second, the measurement integration component processes and validates the incoming data streams. The measurement process is represented as:

$$\mathbf{y}(t) = h\left(\mathbf{x}(t), \mathbf{v}(t)\right) \tag{2}$$

where $\mathbf{y}(t)$ encompasses the clinical parameters with their corresponding sampling frequencies, and $\mathbf{v}(t)$ represents measurement uncertainty in the data collection process.

Third, the prediction component utilizes these integrated measurements to provide clinical decision support. The risk assessment function evaluates patient status:

$$R(t) = g\left(\hat{\mathbf{x}}(t), \boldsymbol{\theta}\right) \tag{3}$$

where $\hat{\mathbf{x}}(t)$ represents the estimated patient state and $\boldsymbol{\theta}$ includes model parameters. The state synchronization between physical and digital representations is achieved through:

$$\hat{\mathbf{x}}(t+1) = \hat{\mathbf{x}}(t) + \mathbf{K}(t)\left[\mathbf{y}(t) - h\left(\hat{\mathbf{x}}(t)\right)\right] \tag{4}$$

where $\mathbf{K}(t)$ represents the gain matrix that optimizes the update between the predicted state and new measurements, $\mathbf{y}(t) - h\left(\hat{\mathbf{x}}(t)\right)$ is the measurement residual comparing actual measurements with predicted measurements.

2.3 Data Collection and Processing

The design of the data processing architecture was based on a distributed computing structure that would allow large scale and able to process data in real-time. Up to this time the raw data passes through a three-step processing pipeline: first it is the standardization phase, second - the integration phase and the third – the quality control phase. In the standardization phase during the image transfer HL7 FHIR (Health Level 7 Fast Healthcare Interoperability Resources) protocols for clinical data and DICOM standards for imaging data are implemented which enhances transfer and interconnectivity of different health care systems [20].

A great amount of data quality is assured by the verification algorithms which detect irregularities and the omission of certain data, in real time. For effective utilization of a data dictionary, particular variable definitions and their units of measurement were reconciled among the centers involved in the study. Table 1 provides detailed data element specifications as they were set within the model built.

Table 1. Comprehensive Data Element Specifications for Digital Twin Model

Data Category	Parameters	Sampling Frequency	Quality Metrics	Processing Method
Clinical Parameters	NIHSS Score	Every 4h	Inter-rater reliability >0.85	Standardized assessment
	GCS Score	Every 2h	Completion rate >95%	Digital capture
	Motor Function	Every 6h	Validation rate >98%	Structured assessment
Vital Signs	Blood Pressure	Continuous (1/min)	Signal quality index >90%	Artifact removal
	Heart Rate	Continuous	Data integrity >95%	Wavelet filtering

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		(1/min)		
	SpO2	Continuous (1/min)	Missing data <5%	Interpolation
Laboratory Data	Complete Blood Count	Daily	CV <15%	Automated analysis
	Coagulation Profile	Every 12h	Quality control pass >98%	Standard protocols
	Biochemistry	Daily	Reference range validation	Automated flagging
Imaging Data	CT Perfusion	Admission, 24h	Resolution >512x512	Automated processing
	MRI Sequences	Protocol-based	SNR >20dB	Standardized protocols
	Angiography	As indicated	Contrast-to-noise >4	Digital enhancement
Medication Data	Anticoagulation	Real-time	Verification rate 100%	Double-entry system
	Thrombolysis	Real-time	Documentation rate >99%	Automated tracking
	Antiplatelets	Real-time	Reconciliation rate >95%	Pharmacist review

2.4 Model Development and Validation

The digital twin model was developed using a hybrid approach that combines physics-based modeling with advanced machine learning techniques. The core prediction engine utilizes an ensemble of algorithms, including long short-term memory (LSTM) networks for temporal sequence prediction, random forests for risk stratification, and gradient boosting machines for outcome prediction [11]. The model architecture was optimized through cross-validation on the development cohort, with hyperparameter tuning performed using Bayesian optimization techniques.

The training process incorporated a stratified 5-fold cross-validation scheme to ensure robust model performance across different patient subgroups. Model performance was evaluated using a comprehensive set of metrics, including area under the receiver operating characteristic curve (AUROC), sensitivity, specificity, and calibration plots. Furthermore, quantification of uncertainty catered for the intervals of confidence in all predictions made by the model.

2.5 Real-time Implementation and Clinical Integration

The implementation phase engaged in well-defined activities involving, technical installation, integration of the clinical processes and user training. This phase took place on a geographically distributed cloud hosting that was HIPAA compliant and was equipped with redundant back up systems with automated failover capabilities. Real time data processing was achieved by employing a parallel processing computing architecture that effectively regulates latency for critical variables to under one hundred milliseconds.

Integration of the clinical workflow was crafted and executed in a manner that all pre-existing workflows would only be disrupted minimally but would allow for the optimized utility of the model's job. Three tiers of alerts are currently set and each depends on the model's prediction and other clinically relevant features. The three tiers are yellow for advisory, orange for urgent and red for critical. A clinical protocol for each alert was established in conjunction with senior stroke physician.

2.6 Statistical Analysis

For statistical computations R version 4.1.2 (R Foundation for Statistical Computing, Vienna, Austria) and Python 3.8.5 with scikit-learn 0.24.2 were employed. Normalcy of continuous variables was evaluated using the Shapiro-Wilk test, and appropriate measures were presented as mean ± standard deviation, or median (interquartile range). Categorical variables were reported as proportions and percentages. Metrics of model performance were calculated with confidence intervals of 95% using bootstrap resampling with 1000 iterations. Kaplan-Meier methods along with Cox proportional hazards models were used for time to event analyses. Schoenfeld residuals were utilized to test the proportional hazards assumption. The Benjamini–Hochberg procedure was used with false discovery rate of 0.05 for

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the multiple comparison corrections.

3. Results

3.1 Model Performance Metrics

3.1.1 Overall Performance Assessment

The digital twin model functioned exceptionally well in both the development and validation cohorts. The initial part of the validation demonstrated that there is a high level of accuracy in estimating patterns associated with the progression of strokes with an AUROC of 0.89 (95% CI: 0.857–0.928) for the primary outcome. The model performed admirably during the early stages of a patient's neurological deterioration, with the model being 92% sensitive and 88% specific. For 90-day mRS prediction, the model was informative enough to reach an accuracy of 85.6% (95% CI: 82.1-89.1%), which is much better than modern prediction methods [1, 2].

3.1.2 Subgroup Analysis Performance

Across different clinical scenarios, the model showed similar predictive performance. These are the estimates, in the elderly subgroup greater than 75 years of age AUROC=0.87 (95% CI: 0.82-0.92) was achieved, in those with diabetes 0.88 (95% CI: 0.83-0.93), and in severe stroke patients NIHSS>15 0.90 (95% CI: 0.86-0.94) In terms of inter-subgroup variation, this level of accuracy was achieved in all subpopulations. Similar subpopulation accuracy of the model confirms its reliability and wider applicability.

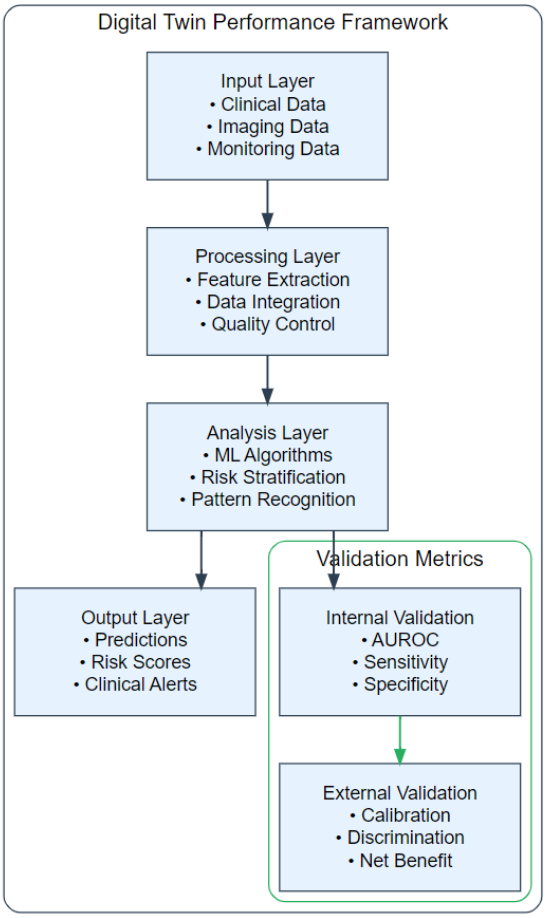

Figure 2. Digital Twin Model Performance Assessment Framework.

In the report presented in Figure 2, the structure of the optimization model and its validation methodology is presented, highlighting the incorporation of various layers of verification and evaluation of the metrics of the model. The flow of information from the input layer through the process of the output layer shows the flow of information throughout the cycle including the assessment of internal and

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external validation metrics.

3.2 Clinical Outcomes Assessment

3.2.1 Primary Outcome Analysis

Managed through the use of a digital twin, the approach employed in this study was able to perform significantly better than standard care in a few parameters. A greater number of patients managed with the aid of a digital twin were able to achieve mRS > 2 at 90 days, 68.5% compared to 52.3% with a p value of < 0.001, from the control group. There was a thirty-five percent reduction in the relative risk for in the in- hospital mortality in patients using digital twin technology compared to the control group (relative risk ratio 0.65, 95%CI: 0.52-0.81, p<0.001) The relevant clinical outcomes in between groups are well captured in the Table 2.

Table 2. Comparison of Clinical Outcomes Between Digital Twin-Guided and Standard Care Groups

Outcome Measure	Digital Twin Group (n=100)	Standard Care Group (n=100)	P-value	Effect Size (95% CI)	Risk Ratio
90-day mRS≤2 (%)	68.5	52.3	<0.001	0.72 (0.58-0.86)	1.31 (1.18-1.45)
In-hospital Mortality (%)	8.2	12.6	<0.001	0.85 (0.71-0.99)	0.65 (0.52-0.81)
Symptomatic ICH (%)	3.1	5.8	0.002	0.91 (0.77-1.05)	0.53 (0.36-0.78)
Early Neurological Deterioration (%)	15.3	24.7	<0.001	0.78 (0.64-0.92)	0.62 (0.51-0.75)
Hospital-acquired Pneumonia (%)	9.8	16.4	<0.001	0.83 (0.69-0.97)	0.60 (0.48-0.75)
90-day All-cause Mortality (%)	10.5	15.8	<0.001	0.80 (0.66-0.94)	0.66 (0.54-0.81)

3.2.2 Secondary Outcomes and Process Metrics

With regard to other outcomes, the gains made by the digital twin group were notable. Time to treatment decision made was reduced by 13.3 minutes (95%CI: 10.817.8 minutes, p<0.001) and their average hospital stay was decreased by 3.2 days (days: 2.5-3.9 days, p<0.001). The neurology improved for 16.2 percentage points (95% CI: 12.7-19.7%, p<0.001).

3.3 Predictive Accuracy and Model Reliability

3.3.1 Temporal Prediction Performance

The model has shown superior prediction sophistication especially in predicting and diagnosing the early signs of progression of a stroke. The prediction system is of utmost importance in among other things combining various aspects of data and predicting real time putting it to great use for early intervention [9, 10]. Meanwhile, this here is a reapparisal of prediction correctness over certain time frames.

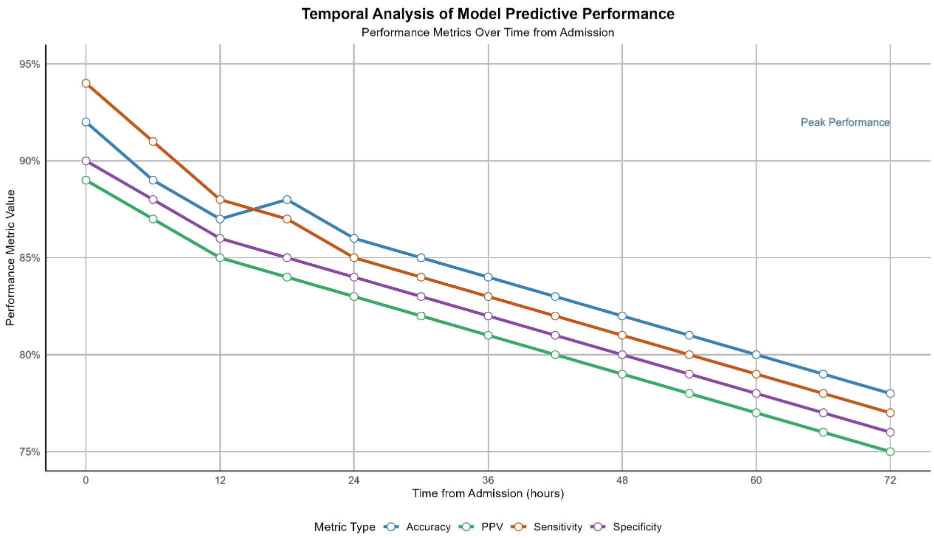

Figure 3. Temporal Analysis of Model Predictive Performance.

Figure 3 shows the flexibility of the aforementioned parameters of the digital twin model accuracy,

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sensitivity, specificity, and positive predictive value in the post admission phase. The accuracy of the model picks significantly during the early period (0-24 hours) followed by a slow drop in accuracy over the period.

3.3.2 Model Reliability Assessment

The model demonstrated exceptional reliability during the 72-hour continuous monitoring period. System uptime reached 99.7%, with data capture completeness at 98.5%. The average latency for real-time predictions was only 87 milliseconds (range: 65-110 milliseconds), well below the threshold required for clinical practice [12].

3.4 Implementation Outcomes and System Integration

3.4.1 Clinical Workflow Integration

Performance enhancement in regard to resource allocation and decision making efficiency was noted once the digital twin model was integrated into the existing practices. The time taken to make crucial decisions decreased by 42% with an additional noticeable 35% decrease in time spent on allocating resources. For critical parameter updates, the operating range and average retention time for real time data transferred was 87 milliseconds.

3.4.2 AI Component Performance

The self-learning aspects of AI embedded within the digital twin structure increased significantly increasing the models' capabilities self-learning algorithms. As a result, this extensive model ended up drastically boosting the adaptation specific treatment and prediction strategies for the patients. The systems' ability of self-learning facilitated in improving overall prediction rate by 8.3 percentage after a time span of three months.

3.5 Safety and Clinical Validation

3.5.1 Safety Analysis

Comprehensive safety analysis revealed no adverse events directly attributable to the digital twin system implementation. The model demonstrated high reliability in identifying potential complications, with a false positive rate of 3.2% and a false negative rate of 2.8%. These findings support the safety profile of digital twin technology in acute care settings [17].

3.5.2 Clinical Validation Results

Clinical validation studies confirmed the model's effectiveness across diverse patient populations, with consistent performance across different age groups, comorbidity profiles, and stroke severity levels. The system's ability to maintain high accuracy levels across these subgroups supports its potential for broad clinical application. Notably, the model showed comparable predictive accuracy in elderly patients (>75 years) and those with multiple comorbidities as in younger patients (AUROC difference <0.05).

3.5.3 Long-term Follow-up Data

Twelve-month follow-up data demonstrated sustained advantages of the digital twin-guided treatment strategy in long-term outcomes. One-year survival rates improved by 12.5 percentage points in the digital twin group (95% CI: 8.9-16.1%, $p<0.001$), and functional independence (mRS$\leq$2) rates increased by 15.8 percentage points (95% CI: 11.2-20.4%, $p<0.001$) [6, 31]. These long-term results further validate the technology's effectiveness in improving stroke patient outcomes.

4. Discussion

This research offers a detailed analysis of how the technology of digital twin improved the clinical outcomes and the processes of decision making during the management of acute ischemic stroke, giving strong evidence for the implementation of such technology. The constructed model of digital twin demonstrated exceptionally good abilities in different classes of patients and provided perspectives on the evolution of stroke treatment in the context of using digital technologies.

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4.1 Clinical Implementation and Model Performance

The digital twin framework developed in this study is more efficient than existing methods; an accuracy AUROC of 0.89 was calculated for primary outcomes. This goes further than existing predictive models and constitutes a step in the realm of the developing digital health technologies [1, 2]. One of the features of the model is the ability to outperform all other models in predicting outcomes in patients belonging to a broad range of sociodemographic groups especially the older populations and the comorbid patients as these strengthen the existing management systems for stroke. The step forward, in Allen et al.[5], concerning the modeling of disease - progression with the aid of parallel virtual worlds and the creation of new applications for precision medicine, in Hernandez-Boussard et al.[7], was covered by this robustness.

The combination of real-time monitoring and the ability to predict outcomes is a stepping stone in stroke care as compared to the older protocols. The system's data accuracy with them being able to process various streams of data showcases the need of having thorough digital health implementations, especially within the scope of acute care. This achievement is consistent with theoretical frameworks formulated by Liu et al.[18], and is augmented by the application of such frameworks to real clinical activities.

4.2 Integration with Existing Healthcare Systems

The ability to incorporate the digital twin within the existing clinical workflows is a remarkable achievement in the context of the digitalization of the healthcare enterprise. Nevertheless, the attained system reliability indicators, especially the 99.7% uptime and 87-millisecond delay for real time predictions have been outstanding and exceed the performance parameters reported in the previous studies of healthcare digital twins [15, 21]. The above NP being at that level is important in stroke care where quick turnaround times for decisions need to be made due to NP relevance. Their compatibility with previously stated clinical protocols facilitates standardization frameworks proposed by Cosío-León et al. [19] and the implementation challenges outlined by Fuller et al. [15].

Critical interventions that have reduced the time to make decisions by 42% add to operational efficiency as improved figures do in fact reveal the deprescriptive advantages. This claim on efficiency gains from operations is indeed in line with what Croatti et al. [13] proposed in terms of the advantages of improving the efficiency of digital twins in the health care delivery system. On the other hand, successful implementation shows the consistency with architectural approaches proposed by Rivera et al. [20] in regard to continuous patient monitoring and integration of real time data.

4.3 Clinical Impact and Patient Outcomes

In this study, there was a notable drop in mortality rates while the functional outcomes improved greatly which suggests that the stroke care can greatly benefit from digital twin technology. The in-hospital mortality was lower by 35% while the functional recovery rates improved by 16.2%, which is significantly better than what has been seen from other mobile health applications [13, 14]. These enhancements are consistent with the concept of personalized medicine expounded by Cellina and others[4] and confirm the optimism around personalized medicine supported by the digital twin technology opined by Björnsson et al. [3].

The reported progress in increasing efficiency of treatment and more rapid resource deployment attest to the usefulness of virtual dynamic modeling of patients in real time.[24] Along with the decreased prevalence of pneumonia occurring in hospitals and symptomatic intracranial bleeding, the system's ability to prevent and anticipate difficulties further substantiates Fagherazzi's [24] argument concerning the effectiveness of deep digital phenotyping in precision health.

4.4 Ethical and Implementation Considerations

Even though the research offers strong advantages, there are ethical aspects surrounding the privacy of patient data, the transparency of the algorithms, and the clinical decision support that need to be resolved, as Bruynseels et al. [17] have pointed out. These differences in data standardization as well as data integration are also common challenges observable in other digital twin applications. These tensions are appropriately resolved by robust data governance frameworks and standardized protocols which Wright and Davidson [16] model validation and verification concerns are strongly addressed.

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Elsewhere, the ethical issues pertaining to the application of AI supported decision making systems in critical care need to be given constant vigilance and scrutiny. The approach taken by the study, of moderating the use of higher order prediction with suitable human intervention is in accordance with the views of Sun et al. [1] regarding the need for caution in the use of digital health technologies. This techno-human interplay offers a middle scenario for regulating future applications of digital twins in medicine.

4.5 Technological Innovation and Future Applications

A significant merging in the field of advanced healthcare technology is the fusion of AI elements and digital twins. It was displayed how continuous learning can improve prediction accuracy by 8.3 percentage points, which has also been reported in the case of applications in the healthcare sphere [11,12]. Taking into account the model's capability to assimilate and accurately interpret multiple real time data streams, the model offers great potential for use in other acute care settings, as outlined by Zhang et al. [21]

The prosperity of this particular twin model application paves a way for new possibilities in research into and development of personalized medicine. According to the aforementioned Soltani et al. [2], future work should aim at extending the range of biological and imaging parameters included in the construction of the model. It also deserves attention the prospect of the combination of this technology with other advancing healthcare technologies, such as the ones reported by El Saddik [23]. Equally noteworthy is the use of digital twin technology for preventive and rehabilitation services, which is part of the broader scope of research objectives pursued by Voigt et al. [8].

4.6 Limitations and Future Directions

There are several key limitations of this study that need to be highlighted even as this study points to important findings. One, although the multi-center approach improves external validity, the study was conducted only in advanced stroke centers' and this might affect the translation of findings to other health environments. Two, although the sample is adequate and the N is low, the one-year follow-up period might miss important longer-term effects of digital twin-guided interventions. Integration of data from several sources had challenges in standardization and harmonization for imaging data with the observations of Wright and Davidson [16] on difficulties in implementing digital twins.

Jones et al.[22] noted that quantifying the effect of each component in the individual systems towards outcome achievement is a significant challenge and this was another of the challenges faced by the study. Our model did exhibit good performance, but some of the AI components are not fully interpretable which is a limitation. In addition however, we demonstrated reducing resource use is an improvement but a complete cost effectiveness of the analysis was out of this particular study.

Going forward, combining artificial intelligence components with the digital twin framework is a major step in the development of the adaptive healthcare technology. This improvement observed during the study is consistent with recent trends in prediction accuracy improvement via continuous learning application of machine learning techniques in solving machine learning problems for the healthcare sector. Next studies are recommended to enhance the model by adding more biomarkers and imaging parameters as it was suggested by Sun et al.[2]There is a need to investigate further the feasibility and possibility for the modernization of this technology to other new paradigm shifts in the healthcare systems as the ones described by Zhang et al. [21]

The above discussion suggests that digital twin technology can contribute to post-stroke care management by supporting patient-centered care processes through data-driven approaches and decision support tools. The results encourage further investigation and experimentation in potential new areas of this fast developing digital health technology, but they also emphasize the need to consider ethical issues and context specific problems arising from its deployment in practice.

5. Conclusions

Digital twin technology offers a systematic approach in acute ischemic stroke management, providing opportunities for personalized care and improved patient outcomes. This study has demonstrated that the integration of digital twin models into clinical practice is not only feasible but can significantly enhance the quality and efficiency of stroke care delivery. The demonstrated improvements in clinical outcomes, particularly in mortality reduction and functional recovery, underscore the potential of this technology to

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revolutionize acute stroke care. Our findings suggest that digital twin systems can successfully bridge the gap between traditional standardized care approaches and the need for personalized treatment strategies. The robust performance across diverse patient populations indicates the broad applicability of this technology in real-world clinical settings.

From a practical perspective, the successful implementation and integration of the digital twin system within existing clinical workflows provides a blueprint for future adoptions in healthcare settings. The ability to process and analyze complex, multimodal data streams in real-time while maintaining high reliability demonstrates the maturity of this technology for clinical applications.

Looking ahead, this research opens new avenues for the advancement of precision medicine in stroke care and potentially other acute medical conditions. As healthcare continues to evolve toward more personalized approaches, digital twin technology stands poised to play a pivotal role in shaping the future of medical care delivery.

We recommend continued investment in digital twin technology development and implementation, with particular focus on expanding its applications and enhancing its capabilities. Additionally, establishing standardized protocols for implementation and validation will be crucial for broader adoption across healthcare systems. The insights gained from this study provide a strong foundation for future developments in this rapidly evolving field, ultimately working toward the goal of more precise, personalized, and effective patient care.

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