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Systems Engineering Process Methodology for Machine Learning and Multi-Criteria Decision Making in Early Detection of Neurological Disorders in Infants

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Abstract: Early detection of risk abnormalities in infants requires integration of clinical evaluation, multimodal data analysis, and structured data retrieval for decision-making. Conventional approaches rely on manual observation, which is subjective, time-consuming, and difficult to implement at scale. Although Machine Learning (ML) has potential for analyzing movement and clinical data, ML outputs are probabilistic and do not directly represent clinical decisions involving various criteria. This research proposes the System Engineering Process Methodology (SEPM) to integrate ML and Multi-Criteria Decision Making (MCDM) to develop a system that detects early-risk abnormalities in neurological disorders in infants. The proposed methodology consists of six stages, namely Requirements Analysis, System Design, Implementation, Testing, Deployment, and Maintenance. The resulting architecture integrates General Movements (GMs) videos and clinical data from the Electronic Health Record (EHR) and neurological inspection. A 3D Convolutional Neural Network (3D-CNN) is used for video analysis, while XGBoost is used for processing tabular clinical data. The predictive results are further integrated into an AHP–TOPSIS-based MCDM layer for risk stratification. The research results are presented as a mapping of systematic ML and MCDM functions in the SEPM cycle,

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with SEPM as the system engineering backbone, ML as the analytical engine, and MCDM as the decision engine. This framework provides a methodological runway for developing a Clinical Decision Support tool to support early detection of neurological risk abnormalities in infants.

Keywords: System Engineering Process Methodology; Machine Learning; Multi-Criteria Decision Making; Detection Risk Neurological; Baby; Clinical Decision Support System

1. Introduction

In the world of pediatrics, detecting early risk abnormalities of neurological disorders in infants, such as Cerebral Palsy (CP), autism spectrum, and developmental delays, has become a main concern for practitioners and parents. A critical window of neuroplasticity occurs in the first years of life, when timely diagnosis and treatment can significantly improve clinical outcomes and children's future quality of life. However, the main challenges in ensuring accurate early detection lie in the complexity of clinical evaluation, the subjectivity of manual observation, and limited access to experienced pediatric neurologists.

In many health facilities, the detection process for neurological abnormalities still relies heavily on manual methods, such as the General Movements Assessment and clinical observation. This process is time-consuming, vulnerable to inter-rater error, and often delayed by long referral queues. In many cases, delays or verification inaccuracies mean babies do not receive the right intervention at the right time, which ultimately hinders the optimization of motor and cognitive development. Therefore, systems must efficiently and accurately detect and validate neurological risk abnormalities in an automated, data-driven way.

The application of Machine Learning (ML) in detecting early neurological abnormalities has shown promising potential, especially in medical image analysis and infant movement pattern analysis. Deep Learning and Computer Vision algorithms can analyze spontaneous baby movement objectively and consistently, identifying motor anomalies as subtle as those that may be overlooked by the human eye. Thus, implementing ML in clinical environments still faces various technical and implementation-related obstacles. Main challenges include the need for a model that is not only accurate but also interpretable (explainable) by a doctor, as well as the ability to balance various clinical criteria such as risk level, inspection cost, and data availability. This is where Multi-Criteria Decision Making (MCDM) becomes crucial. MCDM provides a mathematical framework for evaluating and prioritizing alternative clinical decisions based on multiple, often contradictory criteria, bridging the gap between the ML model's raw output and the final clinical decision.

Although ML and MCDM have been used separately in various sectors, integrating both in the context of early neurological pediatrics detection remains very limited. Most studies have focused only on developing ML models, without considering feature engineering in a comprehensive system that covers the full cycle, from clinical needs analysis and design

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architecture to validation and patient safety. This often causes ML models to fail when adopted in clinical practice because they do not meet standard regulatory requirements.

The development methodology of artificial intelligence in clinical decision support systems has evolved significantly in the last five years. Literature reviews show that integrating Machine Learning (ML), Multi-Criteria Decision Making (MCDM), and Systems Engineering is crucial; however, these approaches are often developed in isolation.

From a methodological computing perspective, deep learning has become standard for analyzing infant movement patterns. [1] developed a meta-analysis methodology showing that Convolutional Neural Network (CNN) architectures and ensemble models such as XGBoost can predict neurodevelopmental outcomes in premature infants with accuracy above 90%. In line with that,proposed a methodology for extracting temporal features using 3D-CNNs to analyze General Movements (GMs) videos. Computing methodology: This approach automates the detection of motor anomalies and smoothness[2]. However, a limitation of pure ML approaches is that they produce only probability-based outputs, which cannot yet translate complex clinical criteria (such as urgency, intervention, and resource availability source power) into structured action recommendations[3].

To bridge the gap between ML probability output and clinical decision-making, Multi-Criteria Decision Making (MCDM) methodologies are increasingly adopted in Clinical Decision Support Systems (CDSS). In a review, systematically mapped methodologies such as the Analytic Hierarchy Process (AHP) and TOPSIS, which are effective for evaluating medical decisions involving mutually exclusive or contradictory (conflicting) criteria [4]. Furthermore, proposed a fuzzy logic-based MCDM approach to handle uncertainty in medical data. Although MCDM methodology has proven robust in evaluating policy, Hospital illness, and medical election tools, its application integrated in real time with ML inference pipelines for pediatric patient risk stratification is still largely unexplored [6].

Developing AI systems in critical domains like health cannot depend only on modeling algorithms; it also requires rigorous engineering. Emphasize that a Software Engineering for AI (SE4AI) methodology is absolutely required to prevent adoption failure due to data drift and mismatches with clinical workflows [6]. As a methodological runway, recently demonstrated the effectiveness of the System Engineering Process Methodology (SEPM), which includes six stages (Requirements Analysis, System Design, Implementation, Testing, Deployment, Maintenance) for developing and validating ML-based systems [7]. The SEPM approach has been shown to increase system efficiency and accuracy significantly. However, previous SEPM implementations have focused on validation products and supply chains and have not yet been adapted to design a hybrid system architecture that integrates ML feature extraction and MCDM risk weighting.

Based on the review methodology above, there is a clear methodological gap: no integrated framework combines Deep Learning architectures (for pattern extraction), MCDM (for multi-criteria risk stratification), and SEPM (as a life-cycle engineering system) into a comprehensive, single detection pipeline for early neurological pediatrics. Previous research has tended to separate

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ML model development from aspects such as multi-criteria decision-making and system life-cycle engineering.

Therefore, a systematic approach, such as the System Engineering Process Methodology (SEPM), is necessary to ensure that a system integrating ML and MCDM can operate optimally, safely, and in compliance with clinical regulations. SEPM provides a framework that includes various stages, starting from requirements analysis, system design, implementation, testing, deployment, and maintenance. This approach makes the identification of neurological biomarkers, clinical decision criteria, and risk monitoring for babies more structured and data-driven.

This study aims to develop an approach based on the System Engineering Process Methodology (SEPM) in Machine Learning and Multi-Criteria Decision Making (MCDM) applications to detect and validate risk abnormalities in neurological disorders in infants. With SEPM implementation, the system is expected to follow a systematic approach, from identifying clinical needs and designing the model to testing accuracy and implementing it in line with standard medical practice and regulations. In addition, this research aims to test the efficiency and accuracy of the early detection process, giving medical professionals and parents confidence in the baby's neurological status.

The novelty of the study lies in applying SEPM to develop an ML- and MCDM-based system for detecting neurological conditions in pediatrics. SEPM provides a more structured approach, from design to implementation, for a system that can be adopted on a large scale in a home setting or clinic. In addition, the research proposes an integration model in which ML performs feature extraction and probability prediction, while MCDM is used for clinical risk stratification and intervention recommendations. Thus, this research is expected to fill a gap in the development of children's health technology and provide solutions that the medical industry can widely adopt.

2. Materials and Method

This study develops a clinical decision support system for early detection of neurological risk abnormalities in infants by integrating Machine Learning (ML) and Multi-Criteria Decision Making (MCDM). This development system adopts the System Engineering Process Methodology (SEPM) framework to ensure the system is not only computationally accurate but also appropriate for clinical and regulatory health needs[7]. SEPM consists of six main stages: Requirements Analysis, System Design, Implementation, Testing, Deployment, and Maintenance.

2.1 Material

Materials used in the study include clinical datasets and devices for model development.

1. Clinical Dataset: The data used consists of motion video recordings of spontaneous baby movements (General Movements) and medical electronic health record (EHR) data, including neurological assessment scores such as the Hammersmith Infant Neurological Examination (HINE). Video data were obtained from a public repository and from the same clinic, and were anonymized to protect patient privacy. The Committee for Health Research Ethics approved the use of these data. This dataset is crucial because movement and clinical data

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quality determine the accuracy of early detection of Cerebral Palsy and other neurodevelopmental disorders [8].

2. Device Software and Tools: ML model development is done using the Python programming language with TensorFlow and PyTorch libraries for deep learning architecture. For MCDM components, Super Decisions software and the scikit-criteria library are used to model the hierarchy and calculate weights. The evaluation system was carried out on an NVIDIA GPU computing environment to speed up model training.

2.2 Method: System Engineering Process Methodology (SEPM)

Implementation of SEPM in the study. This is adapted from the previous methodology used for a validation product, but modified for a context-specific, AI-based system health application. The following is Figure 1. System Engineering Process Methodology (SEPM) in Machine Learning and Multi-Criteria Decision Making (MCDM) applications for detecting and validating neurological risk abnormalities in infants, and a detailed explanation of each stage:

Figure 1. System Engineering Process Methodology (SEPM) in Machine Learning and Multi-Criteria Decision Making (MCDM) applications for detecting and validating neurological risk abnormalities in infants

2.2.1. Requirements Analysis

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This stage aims to identify clinical, technical, and regulatory needs. Clinical needs were identified through interviews with pediatric specialists and child neurologists to understand early detection pathways. Technical needs cover input data specifications for ML (such as video resolution and clinical parameters), as well as MCDM decision criteria.

In the MCDM context, the criteria evaluated cover prediction accuracy, model interpretability, computing cost, and clinical trust level. This analysis produces a document specification that serves as the base design architecture.

2.2.2 . System Design

At the design stage, the architecture system is designed to become two integrated modules:

1. ML Module for Feature Extraction and Prediction: Designed using a Convolutional Neural Network (3D-CNN) to analyze the pattern movement of a baby from video, and XGBoost for processing clinical tabular data. The Deep Learning approach was chosen because it can recognize motor-anomaly difficulties that are not easily detected manually.
2. MCDM Module for Stratification Risk: Designed to use the Analytic Hierarchy Process (AHP) method for weighting clinical criteria and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for ranking alternative decisions (for example: " High Risk - Refer Immediate ", " Moderate Risk - Monitor Periodic", " Risk Low - Action Carry on Routine"). Integrating ML and MCDM ensures that the probability output from ML translates into comprehensive, clinically informed recommendations and follow-up.

2.2.3 . Implementation

Stage implementation involves coding and model training. Video and clinical data are processed through stage preprocessing (normalization, data augmentation, and handling of missing values). The ML model is trained using training and validation datasets with cross-validation to prevent overfitting. In parallel, a panel of neurology and pediatric experts completes matrix comparisons for AHP to determine MCDM criteria weights. Second, the modules are integrated into a web-based application pipeline using the Flask/Django framework, allowing doctors to upload baby data and receive analysis output in real time.

2.2.4 . Testing

Testing was done comprehensively to validate the system's performance before implementation in the clinical environment.

1. ML Model Testing: Evaluated accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) to ensure the model can differentiate between normal and abnormal neurological patterns with minimal error.
2. MCDM Model Testing: Performed sensitivity analysis for test stability, ranking alternatives when weight criteria changed, to ensure that the recommendation system is not biased towards one criterion.

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3. Testing Usability: Used the System Usability Scale (SUS), completed by a doctor child, to evaluate interface usability, ease of interpretation of results, and integration with clinical workflows.

2.2.5 . Deployment

After passing the test, the system is deployed to production (Simulation House Sick or clinic). The system is integrated with the House Sick information system (SIM) or operated as an independent Clinical Decision Support System (CDSS). At this stage, the system is tested in a real-world scenario (pilot project) under strict supervision. Real-time monitoring is carried out to detect potential latency or declining system performance when handling high data loads. Technical documentation and clinical guidance for users are also disseminated on stage to ensure optimal adoption by the medical workforce.

2.2.6 . Maintenance

Stage maintenance aims to ensure the system remains relevant, accurate, and secure over time. Maintenance includes :

1. ML Model Retraining: The ML model is updated regularly using the latest clinical data to adapt to shifts in data distribution (data drift) and improve accuracy over time.
2. Update MCDM Criteria: MCDM weights and criteria are reviewed regularly when clinical, national, or international guidelines related to neurological abnormalities in babies are updated.
3. Maintenance Infrastructure: Update security and cybersecurity to protect patient medical data, and apply bug fixes or feature improvements based on clinician feedback.

3. Results and Discussion

3.1. Results

This research results in an adapted System Engineering Process Methodology (SEPM) design for developing a system to detect early neurological risk abnormalities in infants by integrating Machine Learning (ML) and Multi-Criteria Decision Making (MCDM). The resulting framework does not position ML and MCDM as standalone components; instead, it integrates both into a system engineering cycle that includes needs analysis, system design, implementation, testing, deployment, and maintenance.

The framework is developed to overcome limitations in the early detection process, which still relies heavily on clinical observation and manual assessment, particularly General Movements (GMs), neurological inspection, and integrated medical data recording. In the resulting design, visual data in the form of GM videos and clinical data in the form of Electronic Health Record (EHR), as well as the HINE score, become the main sources of information. The ML component processes the data to produce representative features and predictive information, then passes it to the MCDM components to produce risk stratification and clinical decision recommendations.

3.1.1 Proposed SEPM Framework

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The main result of the study is the Proposed System Engineering Process Methodology (SEPM) Framework for ML–MCDM-Based Early Neurological Risk Detection. This framework adapts the previous SEPM for ML-based system development. It extends it to support system health monitoring by integrating two main components: ML for analytics and MCDM for decision-making.

The resulting framework consists of six stages: Requirements Analysis, System Design, Implementation, Testing, Deployment, and Maintenance. These six stages form a cycle for developing a sustainable system. At every stage, clinical needs, data, ML models, MCDM mechanisms, and the operational system are interconnected. Figure 1 in the script also shows the six-stage structure, highlighting continuous improvement as the connecting element across all development stages.

In the Requirements Analysis stage, the framework begins development by identifying clinical, technical, and regulatory needs. This becomes the basis for determining the type of data required, the characteristics of the output system, decision-making criteria, and users' clinical needs. At the System Design stage, the needs are translated into an integrated system architecture for data processing, ML, MCDM, and clinical decision support.

The implementation stage produces integrated component analytics and decisions in a pipeline system. At this stage, the system processes visual and clinical data, develops ML models, and configures MCDM components. The Testing phase ensures that the ML, MCDM, and interface components can be evaluated before use in the clinical environment. Next, Deployment directs the system to integrate with the environment and maintain service health. At the same time, Maintenance ensures the model, criteria decisions, and infrastructure can be updated in line with data development and clinical needs. This produces a development cycle that does not stop at model building; it continues through the maintenance system.

The main framework produces a clear separation of functions between ML and MCDM. ML extracts patterns and produces predictive information from infant data, while MCDM structures decisions based on clinical and other criteria. This aligns with the novelty of the research, which positions ML for feature extraction and probability prediction, while MCDM is used for risk stratification and intervention recommendations.

3.1.2. Requirements Engineering Results

Requirements Engineering Results show that early detection of neurological risk abnormalities in infants requires integrating visual and clinical information. Based on the identified research needs, four main requirements form the basis of the system design.

First, the system must be capable of analyzing General Movements (GMs) videos objectively. This need arises because analyzing spontaneous baby movements manually can be influenced by the examiner's experience and subjectivity. Because of this, the system needs an analytics component that can consistently recognize movement patterns and the baby's motor characteristics.

Second, the system must integrate visual data with tabular clinical data, especially EHR and HINE scores. The second integration of data sources is required because neurological information

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is represented not only through movement patterns, but also through birth history, clinical characteristics, and neurological examination results. In the resulting framework, visual data and clinical data are treated as two sources of mutual information.

Third, the system needs to go beyond normal/abnormal classification. The system needs to produce risk stratification that can support clinical decision-making. Therefore, MCDM needs to include managing several relevant criteria for clinical decision-making, including prediction accuracy, model interpretability, computational cost, and clinical trust level.

Fourth, the system must have an interface that healthcare professionals, particularly doctors, children, and nurses in the NICU environment, can use. Identification results need to show that the system presents information intuitively so that ML output is not only available as a probability mark, but can be understood and used in the decision-making process.

3.1.3. Integrated ML–MCDM Architecture

The system architecture consists of four main layers: data input and preprocessing, Machine Learning, Multi-Criteria Decision Making, and Clinical Decision Support.

The first layer is the data input and preprocessing layer. The system accepts two main inputs: motion videos of spontaneous infants and clinical data. GM videos undergo stage preprocessing, including frame normalization and baby body area cropping. OpenPose extracts pose representations from baby body skeletons. Meanwhile, clinical data come from EHRs and information inspection systems, such as HINE.

The second is the Machine Learning layer. For video data, a 3D Convolutional Neural Network (3D-CNN) captures spatial and temporal patterns in GM videos; for tabular clinical data, XGBoost processes baby characteristics. Based on the data distribution, each data type is processed using an appropriate approach to capture its characteristics.

The third is the MCDM layer. The output of the ML components is not directly translated into clinical decisions, but is fed into the MCDM mechanism. In this design, the Analytic Hierarchy Process (AHP) determines criterion weights, while the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks alternative decisions. The alternative decisions are categorized as High Risk, Medium Risk, and Low Risk.

The fourth is the Clinical Decision Support layer. In this layer, the results of ML and MCDM processing are translated into information risks that can occur, used by a power medical system designed as a CDSS that can stand Alone or be integrated with the System Information Management House Sick via API.

3.1.4. SEPM Workflow for Early Neurological Risk Detection

The SEPM mapping results show that the detection process for early neurological risk abnormalities can be represented in six mutually exclusive stages.

3.1.4.1. Requirements Analysis

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The first stage produces a system specification based on clinical, technical, and regulatory needs. The main focus is to determine the required data types, the need for video analysis and clinical data, the need for risk stratification, and the need for clinical users. This output stage is a system requirements specification that becomes the basis for stage design.

3.1.4.2. System Design

The second stage produces the ML–MCDM architecture design. At this stage, the system determines the distribution of functions among 3D-CNN for video data, XGBoost for clinical data, AHP for weighting criteria, and TOPSIS for ranking alternative decisions. This stage produces a design architecture and data flow that connects clinical inputs to output decisions.

3.1.4.3. Implementation

Three stages produce the design Implementation of analytical pipelines. Video and clinical data are preprocessed, then used for ML model development. On the MCDM side, AHP uses pairwise matrix comparisons to determine criteria weights. Next, the ML and MCDM components are integrated into a web-based application so the system can receive baby data and generate output analysis.

3.1.4.4. Testing

The fourth stage involves testing the three main components. ML components are evaluated using classification performance metrics, MCDM components are tested through sensitivity analysis to weight changes, while the interface system is evaluated for usability. Thus, testing is notis directed not only at the algorithm, but also at stability decisions and system use.

3.1.4.5. Deployment

The fifth stage produces a design for deployment in clinical environments. The system can be integrated with the system information House Sick or used as a standalone CDSS. The framework also specifies monitoring needs for latency, data load, documentation, technical guidance, and guidance use in Power Health.

3.1.4.6. Maintenance

The sixth stage produces a mechanism for system sustainability. Maintenance covers retraining ML models using the latest data, reviewing return MCDM weights and criteria when clinical guidelines change, and maintaining infrastructure and data security. Thus, the system is not viewed as a finished product after deployment, but as a system that must keep going, updated to follow changes in data, technology, regulations, and clinical needs.

Mapping results show that the six SEPM stages form a sustainable development cycle. Continuous improvement elements connect results to the system through model updates, decision criteria, and infrastructure.

3.1.5. Mapping of ML and MCDM within SEPM

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One of the main results of the study is mapping the connection between Machine Learning and Multi-Criteria Decision Making components in the SEPM cycle. This shows that ML and MCDM are not two separate parallel methods, but rather distinct and interconnected functions that work together within the system pipeline.

At the Requirements Analysis stage, ML and MCDM have not yet been implemented. They are used as main computing components, but both need to be determined. ML is required to analyze patterns from visual and clinical data, while MCDM is required because the output system must consider multiple clinical decision criteria.

At the System Design stage, the second component structure begins to take shape. ML is mapped to two-track analytics, namely 3D-CNN for video GMs and XGBoost for clinical data. MCDM is designed as a decision layer that uses AHP for weighting and TOPSIS for ranking. Thus, the ML–MCDM relationship is designed explicitly at the design stage.

At the Implementation stage, ML functions produce predictive information from raw data, while MCDM uses this information as part of the decision input. This relationship provides a mechanism to transform machine-generated predictions into clinical risk decisions.

At the Testing stage, both components were tested using different approaches. ML focuses on predictive ability, while MCDM focuses on stability when criteria weights change. Thus, validation not only evaluates whether the model can make predictions, but also whether the output can produce consistent decisions.

In the Deployment phase, the ML–MCDM integration is placed in the CDSS environment. System output is not displayed as ML model results alone; instead, it is served in a form that stratifies greater risk and is easily used in the clinical process.

In the Maintenance stage, ML and MCDM also have respective update mechanisms. ML models can be updated using the latest clinical data to anticipate data drift, whereas MCDM criteria and weights can be reviewed when clinical guidelines change.

Mapping the principle of integration in the main research, namely: SEPM regulates cycle life in the system, ML produces evidence or predictions, while MCDM transforms the evidence. This becomes a multi-criteria decision-making process.

3.1.6. Proposed Decision-Making Flow

The final result from the integration of SEPM, ML, and MCDM is a decision-making channel for clinical decisions consisting of seven main stages:

Clinical Data → Preprocessing → ML → Prediction/Probability → MCDM → Risk Stratification → Clinical Recommendation.

The first stage is Clinical Data, namely collecting GM videos and clinical data from the baby's EHR, as well as neurological inspection. Second, the data sources provide the information needed for early detection.

The second stage is Preprocessing. At this stage, the video data is processed through normalization and cropping, and pose information is extracted using OpenPose. Clinical data is also prepared so it can be used by analytical models.

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The third stage is Machine Learning. Video data is analyzed using a 3D-CNN, while tabular clinical data are analyzed using XGBoost. The second component identifies patterns related to neurological risk.

fourth Stage is Prediction/Probability. The results of ML analysis are represented as predictive information or risk probability. At this stage, the system does not yet produce a final clinical decision. This is important because the ML model's probability is not yet directly considered across all required criteria in clinical decision-making.

fifth Stage is MCDM. Predictive information from ML is then combined with criteria using the AHP–TOPSIS approach. AHP determines the level of interest for each criterion, while TOPSIS is used to determine the proximity of each alternative to the ideal solution and produce an ordered preference decision.

The sixth stage is Risk Stratification. The MCDM results are translated into three risk levels: High Risk, Medium Risk, and Low Risk. The third category is designed to make decisions easier for the medical workforce to understand than direct ML probability outputs.

The seventh stage is Clinical Recommendation. Stratification results are further used as the basis for continuing recommendation actions. In the design system, high-risk cases can be directed to the reference immediately, medium-risk cases can be monitored periodically, and low-risk cases can continue routine action. Thus, the output system is more operationally useful and can serve as an information support for medical decision-making.

The flow shows that the framework's main contribution is not just combining two algorithms, but building a functional connection between clinical data, ML-based analysis, MCDM-based retrieval, and clinical recommendations in a one-cycle engineering system.

Conceptually, the relationship can be formulated as :

Clinical Evidence → Computational Evidence → Multi-Criteria Decision → Clinical Action

Clinical Evidence comes from video GMs and clinical data; ML generates computational Evidence; multi-criteria decisions are generated through AHP–TOPSIS; and clinical action is a recommendation carried out based on risk stratification.

3.1. Discussion

Research results show that the System Engineering Process Methodology (SEPM) can be adapted as a methodological framework to integrate Machine Learning (ML) and Multi-Criteria Decision Making (MCDM) for developing systems that detect early-risk abnormalities in neurological disorders in infants. The main contribution of the framework lies not only in selecting an ML algorithm or MCDM method, but in connecting clinical needs, data processing, predictive analysis, decision-making, system implementation, and maintenance in a single development cycle. This approach matters because intelligent systems in the health domain need more than a predictive model; they must also support clinical needs, workflow, power, and sustainability.

3.2.1. SEPM as a Development Backbone System Clinical AI -based

Research results show that SEPM functions as the backbone that regulates the overall system development cycle. The resulting framework consists of six stages: Requirements Analysis, System Design, Implementation, Testing, Deployment, and Maintenance. These six stages provide a structure that allows the development system to start with clinical needs and continue through implementation to post-implementation maintenance. In the file, the previous SEPM used for development system validation was ML-based, but its application in research expanded to include context system health, integrating ML and MCDM.

SEPM's position as a backbone is important because ML and MCDM address different problems. ML finds patterns and produces predictive information from data, while MCDM is used to determine alternatives based on multiple criteria. Without a connecting framework, the second component said, integration can stop at the merge algorithm without addressing user needs, the validation process, integration with clinical systems, and maintenance.

In the proposed framework, SEPM provides structure to determine when and how ML and MCDM are used. Thus, SEPM does not replace ML or MCDM functions, but arranges the connection between them within the system lifecycle. This differentiates the main proposed framework from an approach oriented only toward developing predictive models.

3.2.2. Relevance of ML and MCDM Integration in Detection Neurological Baby

The need to integrate ML and MCDM comes from the characteristics of multimodal, multi-criteria clinical detection processes. Early neurological detection in infants often relies on only one type of information. In this design, we used GM's video data along with EHR data and inspected neurological results such as HINE. Because the data have different characteristics, they require different processing approaches.

ML enables data analysis. For video data, 3D-CNN is used to analyze baby movement patterns, while XGBoost is used for tabular clinical data. This division shows that the framework does not force one algorithm for all data sources, but adapts analytic components to the characteristics of the available data.

However, ML output is in the form of predictions or probabilities, not directly in a clinical decision. In clinical practice, decisions depend not only on prediction results but also on urgency level, interpretability, cost, clinical trust, and the need for continued action. Therefore, MCDM is placed after the ML process to convert predictive information into a decision based on several criteria. This addresses identified methodological gaps in the research, namely the limitations of a pure ML approach in translating probability statistics into structured action recommendations.

3.2.3. The Role of MCDM as a Decision Layer

The framework results show that MCDM is used as the decision layer that processes joint ML output criteria clinically. AHP is used to determine the weight of the criteria of interest, while TOPSIS is used to rank alternative decisions. Designed alternatives consist of three categories: High Risk, Medium Risk, and Low Risk.

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Placing MCDM after ML provides a conceptual basis because decisions are not determined solely by the probability model. On the other hand, predictive information may be one of the next components of evidence considered alongside other criteria. This approach aligns with the use of MCDM in the health field, which aims to support decision-making when multiple criteria must be considered simultaneously.

The use of AHP and TOPSIS also provides a relatively clear structure to the decision-making process. AHP is used for weighting so that each criterion can be represented explicitly. TOPSIS is then used to determine alternatives that are close to the ideal solution. Thus, the process of changing from ML prediction to risk stratification is not direct or arbitrary, but follows a structured decision-making mechanism.

This strengthens the novelty of the research, because the contribution is not just using AHP and TOPSIS together with ML, but positioning MCDM as a formal mechanism to translate ML output into clinical risk stratification in the SEPM lifecycle.

3.2.4. Requirements Engineering as the Basis for Development

Requirements Analysis Results show that the development system started from the clinical needs, not solely from the availability of datasets or an election algorithm. Four main needs identified are GM video analysis for objective assessment, integration of visual and clinical data, risk stratification based on multiple criteria, and an interface usable by doctors, children, and NICU nurses.

This approach matters because health AI systems must suit the intended users and the implementation environment. ML models assessed only on predictive performance are not sufficient. If results are hard to understand, cannot be integrated into clinical workflows, or do not provide relevant information for decision-making, they cannot be used in practice.

In the resulting framework, clinical needs become the basis for determining data needs, analytics needs, decision needs, and interface needs. With Thus, Requirements Analysis functioning as a connector between the clinical domain and the computational domain. This approach also strengthens SEPM as an engineering methodology because every component technology must align with the defined system needs.

3.2.5. Multimodal Data Integration as Part of Architecture

The resulting framework also shows that multimodal data integration is an important part of the development system. Video GMs provide dynamic information about infants' characteristics, while EHR and HINE provide clinical information that can only be obtained through video analysis. Because these data types have different characteristics, the framework separates data processing before integrating it at the decision stage.

GM videos are processed through preprocessing such as frame normalization and body-area cropping, with OpenPose used for skeleton pose extraction. Next, a 3D-CNN analyzes temporal patterns in the video. Tabular clinical data were processed using XGBoost. The architecture shows

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that integration occurs not only at the raw data level, but also through representations and information generated by each component's analytics.

From an engineering perspective, the modular approach provides flexibility because changes in one component do not necessarily require changes across the overall system. For example, a video model can be developed without changing the MCDM weighting mechanism. In contrast, criteria-based decision changes can be performed on the MCDM layer without rebuilding the overall video-processing module.

3.2.6. From Machine Learning to Clinical Decision Support

One contribution of the conceptual framework is a shift in orientation from a system that only produces predictions to one that supports decision-making. In the proposed approach, the flow system consists of:

Clinical Data → Preprocessing → ML → Prediction/Probability → MCDM → Risk Stratification → Clinical Recommendation.

The flow shows that ML prediction is not the final output. Prediction or probability becomes input for MCDM, and MCDM results are used to determine category risks and clinical recommendations, structured in accordance with objective research that treats ML as a component for feature extraction and probability prediction. In contrast, MCDM is used for risk stratification and intervention recommendations.

Approach the own implications important to the interpretation system. Health workers receive not only a probability score but also a risk category, which is needed for decision-making. In research design, risk categories include High Risk, Medium Risk, and Low Risk, each associated with corresponding actions, such as immediate referrals, periodic monitoring, or routine follow-up.

3.2.7. Advantages of SEPM compared to Stand-alone ML or MCDM Approach Alone

Compared conceptually with a stand-alone ML approach, the SEPM–ML–MCDM framework provides broader coverage for further development. A pure ML approach can focus on preprocessing, training, and model evaluation, but it does not yet provide a structure for requirements engineering, deployment, system integration, and maintenance.

Instead, MCDM is used independently to provide a mechanism for ranking or selecting alternatives. Still, it cannot automatically extract complex patterns from videos or clinical data. Therefore, ML and MCDM have complementary functions.

The proposed framework combines these functions under SEPM. ML serves as the analytical engine, MCDM as the decision engine, and SEPM as the system-engineering backbone. This gives a clearer distribution of responsibilities between components and allows modular development.

The approach directly addresses the identified methodological gaps in the research: Deep Learning for pattern analysis, MCDM for risk stratification, and Systems Engineering for the system lifecycle.

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3.2.8. Continuous Improvement and System Sustainability

The discussion also shows that one of SEPM's strengths is including maintenance as an integral part of the methodology. Clinical AI systems may face changes in data distribution (data drift), clinical guidelines, user needs, and data security requirements.

The research framework responds to these conditions through three main mechanisms. First, the ML model can be updated using the latest clinical data. Second, the MCDM weights and criteria can be reviewed and updated if clinical guidelines change. Third, the infrastructure system can be updated to support medical data security and repair functions based on clinician feedback.

This shows that the framework does not treat the system as a finished artifact after implementation. On the other hand, the system is treated as an entity that must keep being evaluated and developed. The concept of continuous improvement, as shown in the SEPM framework, strengthens the methodology as a lifecycle, not just a development procedure.

In the clinical approach, system supporters must adapt to changing medical knowledge and implementation environments. Thus, maintenance becomes an important part of the system's reliability and sustainability.

3.2.9. Methodological Novelty

Based on the results and discussion, the research novelty lies in integrating three layers of the previous methodology, developed separately.

The first layer is SEPM as a system engineering layer, which regulates the development lifecycle from need until maintenance. The second is ML as an analytical layer, used to process visual and clinical data and produce predictive information. The third layer is MCDM as a decision layer, which processes predictive outputs together with clinical criteria to produce risk stratification and recommendations.

Novelty research: no sole combination of 3D-CNN, XGBoost, AHP, and TOPSIS. The main novelty is mapping ML–MCDM functions and interactions across six SEPM stages to form a development methodology for early neurological detection in pediatrics.

Draft in a way that directly fills the methodological gap stated in the introduction section, namely the lack of a comprehensive framework integrating Deep Learning, MCDM, and SEPM into a single detection pipeline for early neurological detection in pediatrics.

3.2.10. Implications and Limitations

Although the framework provides more methodological and comprehensive results, it must be understood within the scope of the research presented here. The framework file provides design integration and a development lifecycle, but validation at an empirical, scale-wide level is still required to prove the framework's generalizability across diverse populations, institutions, and clinical conditions.

The research files include data sources in the form of GM videos and EHR, as well as the use of 3D-CNN, XGBoost, AHP, and TOPSIS. However, details on the complete dataset characteristics, number of subjects, class distribution, model configuration, and external validation

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are not yet explained in sufficient detail. Therefore, the main claim in the article should focus on the methodological framework, while clinical performance and generalization should be positioned as areas requiring further validation.

Limitations: At this time, provide direction for the next study. The framework can be tested using a multicenter dataset with a larger, more diverse population. Testing can also cover validation of the model of stability against data drift, evaluation of user reception, as well as evaluation of the system's impact on the quality of the clinical decision-making process

3.2.11. Overall Discussion

The discussion shows that integrating SEPM, ML, and MCDM provides a more systematic approach to detecting early neurological risk abnormalities in infants. ML provides analytical ability to extract patterns from visual and clinical data; MCDM provides a mechanism to turn information into decisions based on multiple criteria; and SEPM governs the entire process within a development lifecycle system.

The connection can be formulated conceptually as follows:

SEPM = System Engineering Backbone

ML = Analytical/Prediction EngineMCDM = Decision EngineCDSS = Clinical Delivery Layer

This formulation shows that the contribution study is at the architectural and methodological level. SEPM ensures clinical needs drive development, ML produces computational evidence, MCDM converts evidence into risk decisions, and CDSS delivers results to power health with usable information.

Thus, the proposed framework not only integrates technology but also provides a lifecycle approach to ensure that technology can be developed systematically, tested, integrated, and maintained. This approach is expected to become a basis for developing AI-based, structured clinical decision support systems for detecting early neurological risk abnormalities in infants.

4. Conclusion

This study develops the System Engineering Process Methodology (SEPM) as a methodological framework to support the development of a system for early detection of neurological risk abnormalities in infants by integrating Machine Learning (ML) and Multi-Criteria Decision Making (MCDM). The resulting approach overcomes the limitations of approaches that focus only on predictive models by providing a complete system development cycle that includes Requirements Analysis, System Design, Implementation, Testing, Deployment, and Maintenance. The sixth stage integrates clinical needs , technical requirements, model development, decision-making, implementation, and sustainability into a cohesive system.

Research results show that integrating ML and MCDM can create a more structured decision-making channel. On the analytics side, 3D-CNN is used to analyze temporal patterns in General Movements (GMs) videos, whereas XGBoost is used to process tabular clinical data. Next, the ML output feeds into the MCDM module, with AHP used to weight criteria and TOPSIS

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used to rank alternative risks. The integration allows the ML probability output to be translated into stratification (High Risk, Medium Risk, and Low Risk), and the next step can be used as a base for clinical action recommendations.

The main study lies in the architectural methodological approach that connects SEPM, ML, and MCDM in one pipeline. In this regard, SEPM serves as the system-engineering backbone that governs the development lifecycle; ML functions as the analytical and prediction engine to produce information-based data, while MCDM functions as the decision engine to integrate prediction results with various clinical criteria. With this structure, the system does not stop at output classification or probability. Still, it is directed to produce information, risks, and recommendations relevant to the needs of a Clinical Decision Support System (CDSS).

From an implementation standpoint, the framework also supports developing the system in a sustainable way. The maintenance stage covers retraining ML models to anticipate data drift, updating MCDM criteria and weights when clinical guidelines change, and maintaining system security and infrastructure. Thus, the system is positioned to keep updated in accordance with data development, technology, and clinical and environmental implementation needs.

Overall, this research shows that SEPM can be an appropriate approach to integrate predictive ML with mechanism-based decision-making (MCDM) for early detection in pediatric neurology. The resulting framework provides a methodological basis for linking GM video data, clinical data, AI-based analysis, risk stratification, and clinical recommendations in a systematic development process. This directly addresses identified methodological gaps in research, namely the limited frameworks that integrate Deep Learning, MCDM, and SEPM comprehensively in one detection pipeline for early neurological pediatrics.

Although Thus, the proposed framework Still need validation more further on to more clinical datasets large and diverse, validation external to the institution different health, as well as longitudinal evaluation of model stability, change data distribution, acceptance users, and their impact to the decision-making process decision clinical validation the important For ensure that the proposed methodology No only worthy in a way technical, but also has generalization and adequate preparedness For applied to the environment more clinical wide.

This research provides a foundational runway for developing a Clinical Decision Support System based on SEPM–ML–MCDM for early detection of risk abnormalities in infants' neurological development. Furthermore, it can be directed toward multicenter validation, improved model interpretability, integration with health information systems, and prospective evaluation to ensure the security, reliability, and clinical benefits of the system before implementation on a wide scale.

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