

AI and General movements (GMs)

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General movements (GMs) are spontaneous movements of infants up to five months post-term involving the whole body varying in sequence, speed, and amplitude. The assessment of GMs has shown its importance for identifying infants at risk for neuromotor deficits, especially for the detection of cerebral palsy. As the assessment is based on videos of the infant that are rated by trained professionals, the method is time-consuming and expensive. Therefore, approaches based on Artificial Intelligence have gained significantly increased attention in the last years.

general movement assessment

fidgety movements

cerebral palsy

motion sensors

visual sensors

multimodal sensing

physical activity assessment

machine learning

artificial neural network

1. Sensor Modalities Used for General Movement Assessment

The advancement in sensor technology facilitates the automatic monitoring of infants’ movements. Hence, a system using visual or motion sensors can be useful to track these movements to diagnose motor impairments at early stages. This section briefly describes the sensor modalities used in the reviewed studies. [Table 1](#) specifies the sensor modalities used by a particular GMA study.

Table 1. The list of sensors used for the assessment of general movements (GMs) and fidgety movements (FMs).

GMA Study	Meinecke et al. [1]	Rahmati et al. [2]	Adde et al. [3]	Raghuram et al. [4]	Stahl et al. [5]	Schmidt et al. [6]	Ihlen et al. [7]	Gao et al. [8]	Machireddy et al. [9]	McCay et al. [10]	Orlandi et al. [11]	Olsen et al. [12]	Singh and Patterson [13]	Dai et al. [14]	Heinze et al. [15]	Gravem et al. [16]	Rahmati et al. [17]	Tsuji et al. [18]	Philippi et al. [19]	Karch et al. [20]	Adde et al. [21]	Fan et al. [22]	McCay et al. [23]
RGB Camera		X	X	X	X	X	X		X	X	X			X			X	X	X		X		X
Vicon System	X																						
Microsoft Kinect							X			X		X											X
Accelerometer													X		X	X							X

- **RGB Camera** records the color information at the time of exposure by evaluating the spectrum of colors into three channels, i.e., red, green, and blue. They are easily available, portable, and suitable for continuous

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IMU									X	X															OS.
EMTS			X															X		X		X			eras and

reflective markers. These markers are attached to specific, well-defined points of the body. As a result of body movement, infrared light reflects into the camera lens and hits a light-sensitive lamina forming a video signal. It collects visual and depth information of the scene [24].

- **Microsoft Kinect** sensor consists of several state-of-the-art sensing hardware such as RGB camera, depth sensor (RGB-D), and microphone array that helps to collect the audio and video data for 3D motion capture, facial, and voice recognition. It has been popularly used in research fields related to object tracking and recognition, human activity recognition (HAR), gesture recognition, speech recognition, and body skeleton detection. [25].
- **Accelerometers** are sensing devices that can evaluate the acceleration of moving objects and reveal the frequency and intensity of human movements. They have been commonly used to monitor movement disorders, detect falls, and classify activities like sitting, walking, standing, and lying in HAR studies. Due to small size and low-price, they have been commonly fashioned in wearable technologies for continuous and long-term monitoring [26][27].
- **Inertial Measurement Unit (IMU)** is a sensory device that provides the direct measurement of multi-axis accelerometers, gyroscopes, and sometimes other sensors for human motion tracking and analysis. They can also be integrated in wearable devices for long term monitoring of daily activities which can be helpful to assess the physical health of a person [28].
- **Electromagnetic Tracking System (EMTS)** provides the position and orientation quantities of the miniaturized sensors for instantaneous tracking of probes, scopes, and instruments. Sensors entirely track the inside and outside of the body without any obstruction. It is mostly used in image-guided procedures, navigation, and instrument localization [29][30].

2. Classification Algorithms Applied for General Movement Assessment

In machine learning, classification and regression algorithms are used to predict results based upon input data. A classification categorizes the data into predefined classes, whereas regression estimates an outcome from a set of input data. These algorithms are implemented in two phases—training and testing. In each of these phases, the raw data are acquired by sensors. After pre-processing the data, suitable features are extracted to build feature vectors. The feature vectors can be split into train and test datasets. In the training phase, the train dataset is used to train a model. In the testing phase, the trained model is used to predict the results of feature vectors belonging to the test dataset. Finally, the performance of the model is evaluated using different matrices on the test data. [Figure 1](#) shows the essential stages of classification.

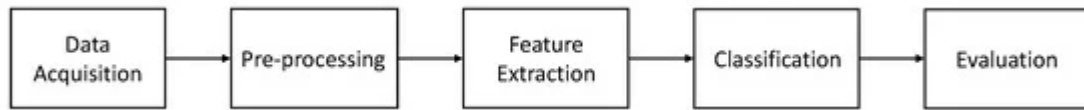


Figure 1. This figure shows necessary steps to solve a classification problem.

Sensors used in data acquisition process for the assessment of GM and FM studies are shown in [Table 1](#). Features extraction process is out of the scope of our topic.

In general, a classification algorithm evaluates the input features to make a decision or diagnosis. The selection of the algorithm depends on many factors, for example, type of data, size of data, and available resources to process the data. This section provides the description of classification algorithms used in GMA studies for the discrimination of infant's movements or impairments.

- **Naive Bayes (NB)** belongs to the group of probabilistic classifiers based on implementing the Bayes' theorem with the simple assumption of conditional independence that the value of a feature is independent of the value of any other feature, and each feature contributes independently to the probability of a class. NB combines the independent feature model to predict a class with a common decision rule known as maximum likelihood estimation or MLE rule. Despite their simplicity, NB classifiers performed well on many real-world datasets such as spam filtering, document classification, and medical diagnosis. They are simple to implement, need a small amount to training data, can be very fast in prediction as compared to most well-known methods [\[31\]](#).
- **Linear Discriminant Analysis (LDA)** is used to identify a linear combination of features that splits two or more classes. The subsequent combination can be used as a linear classifier or dimensionality reduction step before the classification phase. LDA is correlated to principal component analysis (PCA), which also attempts to find a linear combination of best features [\[32\]](#). However, PCA reduces the dimensions by focusing on the variation in data and cannot form any difference in classes. In contrast, it maximizes the between-class variance to the within-class variance to form maximum separable classes [\[33\]](#).
- **Quadratic Discriminant Analysis (QDA)** is a supervised learning algorithm which assumes that each class has a Gaussian distribution. It helps to perform non-linear discriminant analysis and believes that each class has a separate covariance matrix. Moreover, It has some similarities with LDA, but it cannot be used as a dimensionality reduction technique [\[34\]](#).
- **Logistic Regression (LR)** explores the correlation among the independent features and a categorical dependent class labels to find the likelihood of an event by fitting data to the logistic curve. A multinomial logistic regression can be used if the class labels consist of more than two classes. It works differently from the linear regression, which fits the line with the least square, and output continuous value instead of a class label [\[35\]](#).
- **Support Vector Machine (SVM)** is a supervised learning algorithm that analyzes the data for both classification and regression problems. It creates a hyperplane in high dimensional feature space to precisely separate the

training data with maximum margin, which gives confidence that new data could be classified more accurately. In addition to linear classification, SVM can also perform non-linear classification using kernels [\[36\]](#).

- **K-Nearest Neighbor (KNN)** stores all the training data to classify the test data based on similarity measures. The value of K in the KNN denotes the numbers of the nearest neighbors that can involve in the majority voting process. Choosing the best value of k is called parameter tuning and is vital for better accuracy. Sometimes it is called a lazy learner because it does not learn a discriminative function from the training set. KNN can perform well if the data are noise-free, small in size, and labeled [\[37\]](#).
- **Decision Tree (DT)** is a simple presentation of a classification process that can be used to determine the class of a given feature vector. Every node of DT is either a decision node or leaf node. A decision node may have two or more branches, while the leaf node represents a classification or decision. In DTs, the prediction starts from the root node by comparing the attribute values and following the branch based on the comparison. The final result of DT is a leaf node that represents the classification of feature vector [\[38\]](#).
- **Random Forest (RF)** is an ensemble learning technique that consists of a collection of DTs. Each DT in RF learns from a random sample of training feature vectors (examples) and uses a subset of features when deciding to split a node. The generalization error in RF is highly dependent on the number of trees and the correlation between them. It converges to a limit as the number of trees becomes large [\[39\]](#). To get more accurate results, DTs vote for the most popular class.
- **AdaBoost (AB)** builds a robust classifier to boost the performance by combining several weak classifiers, such as a Decision Tree, with the unweighted feature vectors (training examples) that produce the class labels. In case of any misclassification, it raises the weight of that training data. In sequence, the next classifier is built with different weights and misclassified training data get their weights boosted, and this process is repeated. The predictions from all classifiers are combined (by way of majority vote) to make a final prediction [\[40\]](#).
- **LogitBoost (LB)** is an ensemble learning algorithm that is extended from AB to deal with its limitations, for example, sensitivity to noise and outliers [\[41\]](#). It is based on the binomial log-likelihood that modifies the loss function in a linear way. In comparison, AB uses the exponential loss that modifies the loss function exponentially.
- **XGBoost (XGB)** or eXtreme Gradient Boosting is an efficient and scalable use of gradient boosting technique proposed by Friedman et al. [\[41\]](#), available as an open-source library. Its success has been widely acknowledged in various machine learning competitions hosted by Kaggle. XGB is highly scalable as compared with ensemble learning techniques such as AB and LB, which is due to several vital algorithmic optimizations. It includes a state-of-the-art tree learning algorithm for managing sparse data, a weighted quantile method to manage instance weights in approximate tree learning—parallel and distributed computing for fast model exploration [\[42\]](#).

- **Log-Linearized Gaussian Mixture Network (LLGMN)** is a feed-forward kind of neural network that can estimate a posteriori probability for the classifications. The network contains three layers and the output of the last layer is considered as a posteriori probability of each class. The Log-Linearized Gaussian Mixture formation is integrated in the neural network by learning the weight coefficient allowing the evaluation of the probabilistic distribution of given dataset [\[43\]](#).
- **Convolutional Neural Network (CNN)** is a class of ANN, most frequently used to analyze visual imagery. It consists of a sequence of convolution and pooling layers followed by a fully connected neural network. The convolutional layer convolves the input map with k kernels to provide the k -feature map, followed by a nonlinear activation to k -feature map and pooling. The learned features are the input of a fully connected neural network to perform the classification tasks [\[44\]](#).
- **Partial Least Square Regression (PLSR)** is a statistical method that uncovers the relationship among two matrices by revealing their co-variance as minimum as feasible, Rahmati et al. [\[17\]](#) apply it to predict cerebral palsy in young infants. Here, PLSR uses a small sequence of orthogonal Partial Least Square (PLS) components, specified as a set of weighted averages of the X-variables, where the weights are evaluated to maximize the co-variance with the Y-variables and Y is predicted from X via its PLS components or equivalently [\[17\]\[45\]](#).
- **Discriminative Pattern Discovery (DPD)** is a specialized case of *Generalized Multiple Instance* (GMI) learning, where learner uses a collection of labeled bags containing multiple instances, rather than labeled instances. Its main feature is to solve the weak labeling problem in the GMA study by counting the increment of each instance in order to classify it into three pre-defined classes. Moreover, DPD performs the classification based on the softs core proportion rather than a hard presence/absence criteria as in conventional GMI approaches [\[8\]](#).

References

1. Meinecke, L.; Breitbach-Faller, N.; Bartz, C.; Damen, R.; Rau, G.; Disselhorst-Klug, C. Movement analysis in the early detection of newborns at risk for developing spasticity due to infantile cerebral palsy. *Hum. Mov. Sci.* 2006, 25, 125–144.
2. Rahmati, H.; Aamo, O.M.; Stavadahl, Ø.; Dragon, R.; Adde, L. Video-based early cerebral palsy prediction using motion segmentation. In *Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26–30 August 2014*; pp. 3779–3783.
3. Adde, L.; Helbostad, J.L.; Jensenius, A.R.; Taraldsen, G.; Grunewaldt, K.H.; Støen, R. Early prediction of cerebral palsy by computer-based video analysis of general movements: A feasibility study. *Dev. Med. Child Neurol.* 2010, 52, 773–778.

4. Raghuram, K.; Orlandi, S.; Shah, V.; Chau, T.; Luther, M.; Banihani, R.; Church, P. Automated movement analysis to predict motor impairment in preterm infants: A retrospective study. *J. Perinatol.* 2019, 39, 1362–1369.
5. Stahl, A.; Schellewald, C.; Stavdahl, Ø.; Aamo, O.M.; Adde, L.; Kirkerod, H. An optical flow-based method to predict infantile cerebral palsy. *IEEE Trans. Neural Syst. Rehabil. Eng.* 2012, 20, 605–614.
6. Schmidt, W.; Regan, M.; Fahey, M.; Paplinski, A. General movement assessment by machine learning: Why is it so difficult? *J. Med. Artif. Intell.* 2019, 2.
7. Ihlen, E.A.; Støen, R.; Boswell, L.; de Regnier, R.A.; Fjørtoft, T.; Gaebler-Spira, D.; Labori, C.; Loennecken, M.C.; Msall, M.E.; Möinichen, U.I.; et al. Machine Learning of Infant Spontaneous Movements for the Early Prediction of Cerebral Palsy: A Multi-Site Cohort Study. *J. Clin. Med.* 2020, 9, 5.
8. Gao, Y.; Long, Y.; Guan, Y.; Basu, A.; Baggaley, J.; Ploetz, T. Towards Reliable, Automated General Movement Assessment for Perinatal Stroke Screening in Infants Using Wearable Accelerometers. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2019, 3, 1–22.
9. Machireddy, A.; Van Santen, J.; Wilson, J.L.; Myers, J.; Hadders-Algra, M.; Song, X. A video/IMU hybrid system for movement estimation in infants. In *Proceedings of the 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Seogwipo, Korea, 11–15 July 2017; pp. 730–733.
10. McCay, K.D.; Ho, E.S.; Shum, H.P.; Fehringer, G.; Marcroft, C.; Embleton, N.D. Abnormal Infant Movements Classification with Deep Learning on Pose-based Features. *IEEE Access* 2020, 8, 51582–51592.
11. Orlandi, S.; Raghuram, K.; Smith, C.R.; Mansueto, D.; Church, P.; Shah, V.; Luther, M.; Chau, T. Detection of atypical and typical infant movements using computer-based video analysis. In *Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Honolulu, HI, USA, 18–21 July 2018; pp. 3598–3601.
12. Olsen, M.D.; Herskind, A.; Nielsen, J.B.; Paulsen, R.R. Using motion tracking to detect spontaneous movements in infants. In *Scandinavian Conference on Image Analysis*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 410–417.
13. Singh, M.; Patterson, D.J. Involuntary gesture recognition for predicting cerebral palsy in high-risk infants. In *Proceedings of the International Symposium on Wearable Computers (ISWC) 2010*, Seoul, Korea, 10–13 October 2010; pp. 1–8.
14. Dai, X.; Wang, S.; Li, H.; Yue, H.; Min, J. Image-Assisted Discrimination Method for Neurodevelopmental Disorders in Infants Based on Multi-feature Fusion and Ensemble Learning.

- In International Conference on Brain Informatics; Springer: Berlin/Heidelberg, Germany, 2019; pp. 105–114.
15. Heinze, F.; Hesels, K.; Breitbach-Faller, N.; Schmitz-Rode, T.; Disselhorst-Klug, C. Movement analysis by accelerometry of newborns and infants for the early detection of movement disorders due to infantile cerebral palsy. *Med. Biol. Eng. Comput.* 2010, 48, 765–772.
 16. Gravem, D.; Singh, M.; Chen, C.; Rich, J.; Vaughan, J.; Goldberg, K.; Waffarn, F.; Chou, P.; Cooper, D.; Reinkensmeyer, D.; et al. Assessment of infant movement with a compact wireless accelerometer system. *J. Med. Devices* 2012, 6, 021013.
 17. Rahmati, H.; Martens, H.; Aamo, O.M.; Stavadahl, Ø.; Støen, R.; Adde, L. Frequency analysis and feature reduction method for prediction of cerebral palsy in young infants. *IEEE Trans. Neural Syst. Rehabil. Eng.* 2016, 24, 1225–1234.
 18. Tsuji, T.; Nakashima, S.; Hayashi, H.; Soh, Z.; Furui, A.; Shibasaki, T.; Shima, K.; Shimatani, K. Markerless Measurement and evaluation of General Movements in infants. *Sci. Rep.* 2020, 10, 1–13.
 19. Philippi, H.; Karch, D.; Kang, K.S.; Wochner, K.; Pietz, J.; Dickhaus, H.; Hadders-Algra, M. Computer-based analysis of general movements reveals stereotypies predicting cerebral palsy. *Dev. Med. Child Neurol.* 2014, 56, 960–967.
 20. Karch, D.; Kang, K.S.; Wochner, K.; Philippi, H.; Hadders-Algra, M.; Pietz, J.; Dickhaus, H. Kinematic assessment of stereotypy in spontaneous movements in infants. *Gait Posture* 2012, 36, 307–311.
 21. Adde, L.; Helbostad, J.L.; Jensenius, A.R.; Taraldsen, G.; Støen, R. Using computer-based video analysis in the study of fidgety movements. *Early Hum. Dev.* 2009, 85, 541–547.
 22. Fan, M.; Gravem, D.; Cooper, D.M.; Patterson, D.J. Augmenting gesture recognition with erlang-cox models to identify neurological disorders in premature babies. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing, New York, NY, USA, 5–8 September 2012; pp. 411–420.
 23. McCay, K.D.; Ho, E.S.; Marcroft, C.; Embleton, N.D. Establishing pose based features using histograms for the detection of abnormal infant movements. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; pp. 5469–5472.
 24. Vicon. Vicon Motion Systems Ltd. 2020. Available online: <http://www.vicon.com> (accessed on 30 April 2020).
 25. Zhang, Z. Microsoft kinect sensor and its effect. *IEEE Multimed.* 2012, 19, 4–10.

26. Yang, C.C.; Hsu, Y.L. A review of accelerometry-based wearable motion detectors for physical activity monitoring. *Sensors* 2010, 10, 7772–7788.
27. Mathie, M.; Celler, B.G.; Lovell, N.H.; Coster, A. Classification of basic daily movements using a triaxial accelerometer. *Med. Biol. Eng. Comput.* 2004, 42, 679–687.
28. Rodríguez-Martín, D.; Pérez-López, C.; Samà, A.; Cabestany, J.; Català, A. A wearable inertial measurement unit for long-term monitoring in the dependency care area. *Sensors* 2013, 13, 14079–14104.
29. Anagnostoudis, A.; Jan, J. Use of an Electromagnetic Calibrated Pointer in 3D Freehand Ultrasound Calibration; *Proc Radioelektronika*: Brno, Czech Republic, 2005; pp. 3–4.
30. NDI. Electromagnetic Tracking Technology. 2020. Available online: <https://www.ndigital.com/about/ascension-technology-corporation/> (accessed on 30 April 2020).
31. Rish, I. An empirical study of the naive Bayes classifier. In *IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence*; IBM: New York, NY, USA, 2001; Volume 3, pp. 41–46.
32. Martínez, A.M.; Kak, A.C. Pca versus Ida. *IEEE Trans. Pattern Anal. Mach. Intell.* 2001, 23, 228–233.
33. Tharwat, A.; Gaber, T.; Ibrahim, A.; Hassanien, A.E. Linear discriminant analysis: A detailed tutorial. *AI Commun.* 2017, 30, 169–190.
34. Tharwat, A. Linear vs. quadratic discriminant analysis classifier: A tutorial. *Int. J. Appl. Pattern Recognit.* 2016, 3, 145–180.
35. Park, H. An introduction to logistic regression: From basic concepts to interpretation with particular attention to nursing domain. *J. Korean Acad. Nurs.* 2013, 43, 154–164.
36. Noble, W.S. What is a support vector machine? *Nat. Biotechnol.* 2006, 24, 1565–1567.
37. Fix, E. Discriminatory Analysis: Nonparametric Discrimination, Consistency Properties; USAF School of Aviation Medicine: Randolph Field, TX, USA, 1951; pp. 21–49.
38. Utgoff, P.E. Incremental induction of decision trees. *Mach. Learn.* 1989, 4, 161–186.
39. Breiman, L. Random forests. *Mach. Learn.* 2001, 45, 5–32.
40. Freund, Y.; Schapire, R.E. A decision-theoretic generalization of on-line learning and an application to boosting. In *European Conference on Computational Learning Theory*; Springer: Berlin/Heidelberg, Germany, 1995; pp. 23–37.
41. Friedman, J.; Hastie, T.; Tibshirani, R. Additive logistic regression: A statistical view of boosting (with discussion and a rejoinder by the authors). *Ann. Stat.* 2000, 28, 337–407.
42. Chen, T.; Guestrin, C. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM Sigkdd International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA,

USA, 13–17 August 2016; pp. 785–794.

43. Tsuji, T.; Fukuda, O.; Ichinobe, H.; Kaneko, M. A log-linearized Gaussian mixture network and its application to EEG pattern classification. *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* 1999, 29, 60–72.
44. Kozma, R.; Alippi, C.; Choe, Y.; Morabito, F.C. *Artificial Intelligence in the Age of Neural Networks and Brain Computing*; Academic Press: Cambridge, MA, USA, 2018.
45. Wold, S.; Ruhe, A.; Wold, H.; Dunn, W., III. The collinearity problem in linear regression. The partial least squares (PLS) approach to generalized inverses. *SIAM J. Sci. Stat. Comput.* 1984, 5, 735–743.

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