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Machine Learning Algorithms for Prediction of Ambulation and Wheelchair Transfer Ability in Spina Bifida

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Abstract

Objective: To determine which statistical techniques enhance our ability to predict ambulation and transfer ability in people with spina bifida (SB).

Design: Retrospective cohort study.

Setting: Thirty-five US outpatient SB clinic sites.

Participants: Individuals (n=4589) with SB aged 5–73 years (median age=13.59y).

Intervention: Not applicable.

Main Outcome Measures: Ambulation ability, which consisted of the following categories: community ambulators, household ambulators, therapeutic ambulators, and nonambulators.

Secondary Outcome: Wheelchair transfer ability, as defined by the ability to transfer in and out of a wheelchair unassisted.

Results: A recurrent neural network (RNN) using a multilayer perceptron discarded 76 cases during case processing, resulting in 4513 that were run through the RNN. The predictions in the resulting testing dataset were 83.22% accurate. Recall was 93.21% for community ambulators, 10.00% for household ambulators, 23.96% for therapeutic ambulators, and 76.70% for nonambulators. Precision was 85.34% for community ambulators, 16.05% for household ambulators, 16.67% for therapeutic ambulators, and 93.47% for nonambulators. Total predictions included 68.39% for community ambulators, 2.25% for household ambulators, 3.83% for therapeutic ambulators, and 25.53% for nonambulators. Correspondingly, the model accurately classified 70% of wheelchair transfers while correctly identifying 97.3% of those able to transfer unassisted.

Conclusions: RNN models hold promise for the prediction of functional outcomes such as ambulation and transfer ability in people with SB, particularly for community ambulators and

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nonambulators. Compared with the previous work using traditional logistic regression approaches which misclassified 16% of cases, the RNN resulted in greater prediction accuracy with fewer than 7% of cases misclassified.

Keywords

Ambulation; Machine learning; Myelomeningocele; Population outcomes; Registries; Rehabilitation; Spina bifida; Spinal dysraphism; Transfer; Walking; Wheelchair

The incidence of spina bifida (SB) is approximately 3 in 10,000 live births in the United States.¹ SB is a common congenital condition characterized by varying degrees of incomplete neural tube closure, with myelomeningocele (MMC), defined by spinal cord protrusion through the unfused vertebral column, being the most common and severe form.^{2–6} In addition, SB is the most common neural tube defect that is compatible with life and results in permanent disability, with a prevalence of approximately 166,000 patients in the United States.¹ People with SB identify mobility, including the ability to transfer and ambulate, as being essential to independence, employment, and quality of life.^{7–11} According to the scale published by Hoffer et al,¹² ambulation ability can be classified into the following categories or levels of function: ability to ambulate independently in the *community*; ability to ambulate in the *household*; ability to ambulate *therapeutically* (with a therapist in household or school); or *nonambulators*. Prior research has shown that ambulation ability is related to age, motor or lesion level, shunt status (or history of hydrocephalus), hip and knee contractures, and spasticity.^{8–10,13–15} In addition, approximately 60% of patients with SB use wheelchairs, depending on the severity of their condition.^{10,16}

Historically, most models created to predict ambulation ability in people with SB included limited input variables, primarily age and motor level, shunt status (or history of hydrocephalus), hip and knee contractures, spasticity, iliopsoas and quadriceps muscle strength, and surgical intervention.^{17–20} Although several models for predicting ambulation classification based on age and specific motor and sensory level findings have been published and validated, their accuracy (ability to correctly classify) is low. In addition, the results are limited by a small sample size (often 100 or fewer participants), cross-sectional design, and a descriptive nature that is not able to control for confounding factors. Further, although age is widely used in prediction rules, its role and interactions have not been adequately evaluated. Research using traditional regression-based approaches to accurately predict ambulation ability misclassified 16% of cases and suggests that future prediction rules may benefit from the addition of variables and/or alternate techniques.²¹ Using more advanced analytical techniques as described further in this paper may also improve the prediction accuracy for ambulation ability.

Although the ability to transfer was also listed as an essential component of quality of life for those with SB, literature involving transfer ability in this population has been sparse.²² Verhoef et al²³ found that young adults with SB without hydrocephalus or lesions below L2 were able to transfer independently, whereas 38% of those with hydrocephalus and lesions at L2 or above needed assistance to transfer. In a recent study on the change in transfer ability,

McKernan et al²² used a more modern statistical method and found that motor level was the most important predictor of baseline transfer ability, followed by patient age.

Understanding which factors contribute to ambulatory ability over time may help guide rehabilitation interventions. The purpose of our study was to determine which statistical techniques enhance our ability to predict ambulation and transfer ability in people with SB. We hypothesized that machine learning models, such as recurrent neural networks (RNNs), will improve the accuracy of predicting ambulation and transfer ability compared with traditional, regression-based approaches.

Methods

This study was a retrospective analysis using baseline data from the National SB Patient Registry (NSBPR). The dataset included 6823 unique patients from visits at 35 clinic sites occurring between 2009 and 2017. After omitting patients aged <5 years and patients who had only one recorded visit, we arrived at a sample size of 4589 for the study. The RNN models for nominal (ambulation ability levels) outcomes were evaluated according to model fit and classification accuracy. Input variables from the first visit recorded in the registry were used to predict the outcome variables of ambulation and transfer ability at the most recent visit.

In the present analysis, variables from the NSBPR dataset were used, covering a range of sociodemographic factors, clinical characteristics, and functional outcomes. Sociodemographic factors included age, sex, race, and ethnicity. SB subphenotype was categorized into 6 types: MMC, meningocele, fatty filum with tethered cord, lipomyelomeningocele, split cord malformation, and terminal myelocystocele. For analysis, the SB subphenotype was collapsed into a binary variable with an MMC group and a non-MMC group. The number of orthopedic and neurosurgical procedures was also considered, with neurosurgeries classified as either “shunt neurosurgeries” (involving cerebral shunts) or “non-shunt neurosurgeries” (not involving cerebral shunts). Functional motor level, reported separately for the left and right sides, was classified as thoracic (flaccid lower extremities), high lumbar (hip flexion present), mid lumbar (knee extension present), low lumbar (foot dorsiflexion present), or sacral (foot plantar flexion present). In cases where motor levels differed between sides, the more severe side was used. The insurance status was categorized as private (including commercial plans and TRICARE), public only (Medicaid, Medicare, and associated state programs), or “other,” which included supplementary insurance and the uninsured. In addition, binary variables were used to indicate whether the participant used a wheelchair or brace.

The outcome variables included ambulation ability and wheelchair transfer ability. Ambulation ability was classified into 4 categories: community ambulators, household ambulators, therapeutic ambulators, and nonambulators. Wheelchair transfer ability was assessed for those who used wheelchairs most of the time (therapeutic and nonambulators) and was categorized as either able to transfer unassisted from a wheelchair to another level surface or not able to do so (table 1).

Patients were included based on the following characteristics

Inclusion criteria—SB phenotype of MMC and non-MMC (meningocele, fatty filum with tethered cord, lipomyelomeningocele, split cord malformation, or terminal myelocystocele) (these are the only subphenotypes eligible for the registry).

Exclusion criterion—Children aged <5 years were excluded because obtaining accurate manual muscle testing is relatively unreliable until the age of 5 years.²⁴ In addition, patients with only one recorded visit were excluded to ensure that we were assessing future ambulation capabilities.

Statistical analyses—All statistical analyses were conducted using IBM SPSS Statistics version 28.0.^a A multilayer perceptron (MLP) RNN was used to predict ambulation ability. The MLP RNN was run twice, using 2 different training datasets. The first training dataset was randomly selected from the full dataset, making up 70% of valid cases. Because there were large differences in frequencies between ambulation categories, this is considered an unbalanced training dataset. A second, balanced training dataset was created where the frequencies of ambulation ability values were all equal. The frequency itself was determined by taking 70% of the least frequent variable, and cases were randomly selected from ambulation group. Using a validation dataset is one way to address potential overfitting. Once the training datasets were designated, all cases were run through the MLP, and prediction accuracy, recall, and precision were assessed. Accuracy measures how well the model predicts the outcome variable and is measured by dividing all correct predictions by the total number of predictions. Recall measures the ability of the model to identify true positives and is calculated by dividing the number of correctly predicted positives by the number of actual positives. Precision measures how often the model correctly predicts a class and is calculated by dividing the number of correct predictions from a class by the number of total predictions of that class. RNN models have the advantage of identifying hidden trends or relationships in large datasets with many independent variables that are nonlinear. They consist of several layers: input, output, and one or multiple hidden layers, with weights attached to each connection.²⁵ Data are offered to the network via the input layer, which communicates to one or more hidden layers where the actual processing is completed by a system of weighted connections. The hidden layers then link to an output layer, where the final solution can be found. The nodes are connected from the input layer outward, and the error between the predicted output value and the actual value is fed back through the network to update the initial values assigned to the weights (see RNNs with 1 or 2 hidden layers below). The goal of this process is to minimize the error between anticipated and expected outputs. The ability to recognize patterns was trained in the hidden layers, and when new relationships are presented, the model is able to identify them. The RNN models provide measures of features' importance in accounting for outcome variance, as illustrated in fig 1.²⁶ The RNN models can use many activation functions. The choice of activation function in the hidden layer will control how well the network model learns the training dataset. The choice of activation function in the output layer will define the type of predictions the model can make. In this analysis, a single-hidden layer MLP transformation function was used. MLPs are good for problems where inputs are assigned a class or label, or where a real-valued quantity is predicted given a set of inputs. MLPs can learn complex

patterns and relationships in structured data because they can handle input data with fixed dimensions and independent features. They can also approximate any continuous function, not just linear functions, by combining several neurons in at least 3 layers. MLPs are scalable, easy to implement, and can handle large amounts of input data well. They can make quick predictions after training and achieve the same accuracy ratio even with smaller samples. Traditionally, an MLP can be viewed as a logistic regression classifier where the input is first transformed using a learned nonlinear transformation Φ . This transformation projects the input data into a space where it becomes linearly separable. A single-hidden layer is sufficient to make MLPs a universal approximator.

Formally, a one hidden layer MLP is a function $f: R^D \rightarrow R^L$, where R is a set of real vectors, D is the size of input vector x , and L is the size of the output vector $f(x)$, such that in matrix notation

$$f(x) = G(b^{(2)} + W^{(2)}(s(b^{(1)} + W^{(1)}x))),$$

with bias vectors $b^{(1)}$ and $b^{(2)}$; weight matrices $W^{(1)}$ and $W^{(2)}$, and activation functions G and s . The bias vector is a set of values (one for each neuron) added to the weighted input before the activation function is applied.

The vector $h(x) = \Phi(x) = s(b^{(1)} + W^{(1)}x)$ constitutes the hidden layer of the nonlinear transformation, Φ . The hidden layer vector is composed of the activation function, s , which pulls in both bias vectors, $b^{(1)}$; and weight matrices, $W^{(1)}$. To avoid poor initial values, such as a saddle point where gradients are zero but the value is suboptimal, weights are initialized randomly. This random initialization is key to escaping local optima and allows gradient descent to update the weights effectively. The weights are initialized as random matrices drawn from a Gaussian distribution. The dimensions of the weight matrices are determined by the dimensions of the input data and the number of classes. Finally, the output vector is then obtained as $o(x) = G(b^{(2)} + W^{(2)}h(x))$, which is a prediction (in our case, category) based on the probability of class membership, derived from the inputs transformed by the hidden layer $h(x)$, activation function, (G), bias vector $b^{(1)}$, and weight matrices, $W^{(2)}$.

To train an MLP, all of the parameters must be obtained. The set of parameters to learn is the set: $\theta = \{W^{(2)}, b^{(2)}, W^{(1)}, b^{(1)}\}$, which included collection of the weight matrices and the bias vector.

Results

Demographics and baseline characteristics

The RNN using MLP resulted in the highest overall classification accuracy for ambulation ability. Because of missingness in one or more of the input variables, the MLP discarded 76 cases during case processing, resulting in 4513 that were run through the RNN. The training was made up of 3179 cases and a testing set included 1334. The predictions using

the unbalanced training dataset were 80.21% accurate. Recall was 95.72% for community ambulators, 3.92% for household ambulators, 12.36% for therapeutic ambulators, and 86.40% for nonambulators. Precision was 78.04% for community ambulators, 28.57% for household ambulators, 68.75% for therapeutic ambulators, and 87.02% for nonambulators. Total predictions included 66.57% for community ambulators, 1.05% for household ambulators, 1.20% for therapeutic ambulators, and 31.18% for nonambulators.

The balanced training set was made up of 913 cases and the testing set included 3600 cases. The predictions using the balanced training dataset were 83.22% accurate, a 3.01% point increase. Recall was 93.21% for community ambulators, 10.00% for household ambulators, 23.96% for therapeutic ambulators, and 76.70% for nonambulators. Precision was 85.34% for community ambulators, 16.05% for household ambulators, 16.67% for therapeutic ambulators, and 93.47% for nonambulators. Total predictions included 68.39% for community ambulators, 2.25% for household ambulators, 3.83% for therapeutic ambulators, and 25.53% for nonambulators (table 2).

When examining the model's ability to correctly classify wheelchair transfers (n=1546), the overall predictions in the unbalanced dataset were 70% accurate (table 3). The model correctly classified 97.3% of those able to transfer unassisted while classifying only 3.6% of those unable to transfer. Balancing the data resulted in an improvement in classification accuracy for inability to transfer (29.1% correctly classified).

Discussion

To our knowledge, this is the first study of ambulation and transfer ability prediction in SB using machine learning methodology. The RNNs use of multidomain predictors, such as sociodemographic and clinical variables, leads to better prediction compared to a traditional regression-based approach in our prior work.²¹ The machine learning model's ability to include a large number of predictors and identify complex, nonlinear relationships between predictors is particularly useful in explaining latent relationships between clinical and sociodemographic factors. The inclusion of clinical and sociodemographic factors in this model increased its accuracy.

The guidelines for the Care of People with SB recommend monitoring ambulation status and prescribing interventions such as physical therapy or assistive technology when ambulatory ability is declining.²⁷ However, to date, clinicians lack the proper decision support tools to help them make decisions about what interventions to prescribe and when based on a patient's current condition and likelihood of ambulating in the future. Models such as the one used in this study could be used in clinical decision making to prognosticate whether individuals will be ambulatory at a future point in time and consider how to intervene earlier. The guidelines, published in 2018, also identify research gaps in the literature. Further research with this type of model can address several knowledge gaps. These gaps include identifying which therapies can be used to optimize mobility, using patient characteristics to develop anticipatory developmental milestones and track them, and identifying which mobility interventions such as orthotics should be introduced for individuals who have

different characteristics and complications and how patient factors such as weight gain or orthopedic changes affect mobility over time.

Study limitations

There are several limitations of this study. Our study population is limited to patients who receive care in large, academic medical centers. In addition, we have limited our data to only include patients over the age of 5 years. Although our sample size is large for SB research, it is not large according to the current machine learning standards. Although it is well known that a large sample size is required to effectively use machine learning to solve problems without incorporating excessive bias, an exact methodology for determining the sample size required to effectively train and test a machine learning model has not been established. A general guideline suggests having at least 20 times the number of observations as features, which we have established. Furthermore, the categories within ambulation classification levels are unbalanced, with most of our study population consisting of community and nonambulators. The models did not predict the “in-between” categories of household and therapeutic ambulation well, which is something we would like to investigate in the next iteration of research. We were able to train the models to identify those who can ambulate well and those who cannot ambulate at all, but the models struggled to identify those who fell somewhere in between. With additional data points, the models may be able to more accurately classify household and therapeutic ambulators.

Conclusions

Our findings suggest that RNN models demonstrate utility for prediction of functional outcomes such as ambulation and transfer ability in people with SB, particularly for community and nonambulators. Compared to the previous work using traditional approaches, the machine learning model resulted in greater accuracy in predicting ambulation ability for people with SB, with less than 7% of cases misclassified using the RNN (averaged across categories) compared with 16% misclassified from the logistic regression model. Using more advanced analytical techniques, as described further in this paper, may also improve prediction accuracy for other outcomes of SB, such as pain and quality of life measures.

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List of abbreviations:

MLP	multilayer perceptron
MMC	myelomeningocele
NSBPR	National Spina Bifida Patient Registry
SB	spina bifida

References

1. Fletcher JM, Brei TJ. Introduction: spina bifida—a multidisciplinary perspective. *Dev Disabil Res Rev* 2010;16:1–5. [PubMed: 20419765]
2. CDC. Data & statistics on spina bifida. 2018. Available at: <https://www.cdc.gov/ncbddd/spinabifida/data.html>. Accessed January 09, 2022.
3. Copp AJ, Adzick NS, Chitty LS, Fletcher JM, Holmbeck GN, Shaw GM. Spina bifida. *Nat Rev Dis Primers* 2015;1:15007. [PubMed: 27189655]
4. Mohd-Zin SW, Marwan AI, Abou Chaar MK, Ahmad-Annuar A, Abdul-Aziz NM. Spina bifida: pathogenesis, mechanisms, and genes in mice and humans. *Scientifica (Cairo)* 2017;2017:5364827. [PubMed: 28286691]
5. Norkett W, McLone DG, Bowman R. Current management strategies of hydrocephalus in the child with open spina bifida. *Top Spinal Cord Inj Rehabil* 2016;22:241–6. [PubMed: 29339864]
6. Pillay PK, Awad IA, Little JR, Hahn JF. Symptomatic Chiari malformation in adults: a new classification based on magnetic resonance imaging with clinical and prognostic significance. *Neurosurgery* 1991;28:639–45. [PubMed: 1876240]
7. Bakaniene I, Prasauskiene A, Vaiciene-Magistris N. Health-related quality of life in children with myelomeningocele: a systematic review of the literature. *Child Care Health Dev* 2016;42:625–43. [PubMed: 27381478]
8. Bartonek A, Saraste H. Factors influencing ambulation in myelomeningocele: a cross-sectional study. *Dev Med Child Neurol* 2001;43:253–60. [PubMed: 11305403]
9. Dicianno BE, Bellin MH, Zabel AT. Spina bifida and mobility in the transition years. *Am J Phys Med Rehabil* 2009;88:1002–6. [PubMed: 19935183]
10. Dicianno BE, Karmarkar A, Houtrow A, et al. Factors associated with mobility outcomes in a national spina bifida patient registry. *Am J Phys Med Rehabil* 2015;94:1015–25. [PubMed: 26488146]
11. Schoenmakers MA, Uiterwaal CS, Gulmans VA, Gooskens RH, Helders PJ. Determinants of functional independence and quality of life in children with spina bifida. *Clin Rehabil* 2005;19:677–85. [PubMed: 16180605]
12. Hoffer MM, Feiwell E, Perry R, Perry J, Bonnett C. Functional ambulation in patients with myelomeningocele. *J Bone Joint Surg Am* 1973;55:137–48. [PubMed: 4570891]
13. Bartonek A. Motor development toward ambulation in preschool children with myelomeningocele – a prospective study. *Pediatr Phys Ther* 2010;22:52–60. [PubMed: 20142706]

14. Danielsson AJ, Bartonek A, Levey E, McHale K, Sponseller P, Saraste H. Associations between orthopaedic findings, ambulation and health-related quality of life in children with myelomeningocele. *J Child Orthop* 2008;2:45–54. [PubMed: 19308602]
15. Oakeshott P, Hunt GM, Poulton A, Reid F. Open spina bifida: birth findings predict long-term outcome. *Arch Dis Child* 2012;97:474–6. [PubMed: 22121146]
16. Dicianno BE, Gaines A, Collins DM, Mobility Lee S. assistive technology use, and social integration among adults with spina bifida. *Am J Phys Med Rehabil* 2009;88:533–41. [PubMed: 19542778]
17. Dicianno BE, Kurowski BG, Yang JM, et al. Rehabilitation and medical management of the adult with spina bifida. *Am J Phys Med Rehabil* 2008;87:1027–50. [PubMed: 18923330]
18. Alabi NB, Thibadeau J, Wiener JS, et al. Surgeries and health outcomes among patients with spina bifida. *Pediatrics* 2018;142: e20173730. [PubMed: 30158199]
19. Bloemen MA, Verschuren O, van Mechelen C. Personal and environmental factors to consider when aiming to improve participation in physical activity in children with spina bifida: a qualitative study. *BMC Neurol* 2015;15:11. [PubMed: 25886148]
20. Johnson KL, Dudgeon B, Kuehn C, Walker W, et al. Assistive technology use among adolescents and young adults with spina bifida. *Am J Public Health* 2007;97:330–6. [PubMed: 17194874]
21. Davis WA, Zigler CK, Crytzer TM, Izzo S, Houtrow AJ, Dicianno BE. Factors associated with ambulation in myelomeningocele: a longitudinal study from the national spina bifida patient registry. *Am J Phys Med Rehabil* 2020;99:586–94. [PubMed: 32209832]
22. McKernan G, Izzo S, Crytzer TM, Houtrow AJ, Dicianno BE. Relationship between motor level and wheelchair transfer ability in spina bifida: a study from the national spina bifida registry. *Arch Phys Med Rehabil* 2020;101:1953–60. [PubMed: 32682935]
23. Verhoef M, Barf HA, Post MW, van Asbeck FW, Gooskens RH, Prevo AJ. Functional independence among young adults with spina bifida, in relation to hydrocephalus and level of lesion. *Dev Med Child Neurol* 2006;48:114–9. [PubMed: 16417666]
24. Schoenmakers MA, Gulmans VA, Gooskens RH, Pruijs JE, Helders PJ. Spinal fusion in children with spina bifida: influence on ambulation level and functional abilities. *Eur Spine J* 2005;14:415–22. [PubMed: 15258836]
25. Liu Y, Yao X. Towards designing neural network ensembles by evolution. In: *International Conference on Parallel Problem Solving from Nature*, Springer; 1998.
26. Müller AC, Guido S. *Introduction to machine learning with Python: a guide for data scientists*. Sepastopol, California: O'Reilly Media, Inc.; 2016.
27. Spina Bifida Association. Guidelines for the care of people with Spina Bifida. 2018. Available at: <http://www.spinabifidaassociation.org/guidelines/>. Accessed February 26, 2024.

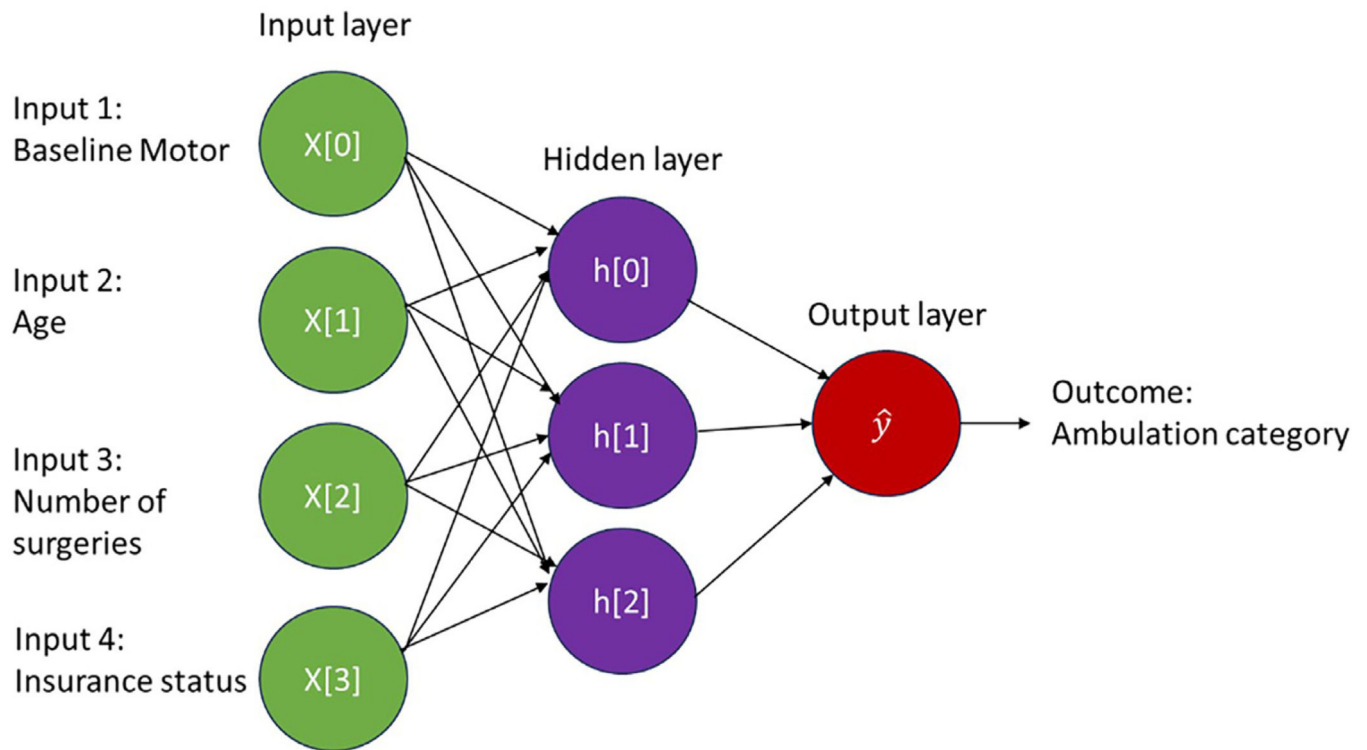
**Fig 1.**

Illustration of neural network model to predict ambulation category. The input layer receives information from the outside world (predictors such as baseline motor level, age, number of surgeries, insurance status) and the input nodes process the data. Each node, x , is represented by a number [0]-[3]. The hidden layer transforms inputs from the input layer to the output layer, by assigning weights (h) based on the strength of the signal (variable importance) to the inputs and passing them through an activation function (MLP). The output layer ($\hat{y}$) is the final layer that contains the model's predictions (ambulation category) based on the learned representations from the hidden layers.

Table 1

Demographics and baseline characteristics

Baseline Variables	MMC (n=3707)	Non-MMC (n=882)
Median age (IQR)	13.59 (9.25)	11.63 (8.09)
% Female individuals	52.00	54.00
% Hispanic or Latino	21.00	20.80
% White	84.00	78.00
% Black	9.70	6.40
% Asian	2.40	10.30
% American Indian	0.90	1.60
% Native Hawaiian	0.20	0.10
% Able to transfer unassisted (n=1222)	72.6	n/a
Baseline functional motor level: sacral	19.20%	68.60%
Baseline functional motor level: low lumbar	16.80%	15.00%
Baseline functional motor level: mid lumbar	31.10%	11.50%
Baseline functional motor level: high lumbar	11.20%	2.70%
Baseline functional motor level: thoracic	21.70%	2.30%
Baseline ambulation ability: community ambulators	46.40%	91.30%
Baseline ambulation ability: household ambulators	9.20%	2.70%
Baseline ambulation ability: therapeutic ambulators	8.40%	2.20%
Baseline ambulation ability: nonambulators	36.00%	3.90%

Abbreviations: IQR, interquartile range; MMC, myelomeningocele.

Comparing the testing classification matrices between balanced and unbalanced training distributions for ambulation ability

Table 2

Unbalanced Testing					
Baseline Variables	Community	Household	Therapeutic	Nonambulator	Recall
Community	693	5	1	25	95.72%
Household	83	4	4	11	3.92%
Therapeutic	55	5	11	18	12.36%
Nonambulator	57	0	0	362	86.40%
Precision	78.04%	28.57%	68.75%	87.02%	
Overall accuracy					80.21%
Balanced Testing					
Baseline Variables	Community	Household	Therapeutic	Nonambulator	Recall
Community	2101	53	65	35	93.21%
Household	88	13	16	13	10.00%
Therapeutic	52	9	23	12	23.96%
Nonambulator	221	6	34	859	76.70%
Precision	85.34%	16.05%	16.67%	93.47%	
Overall accuracy					83.22%

Table 3
Comparing the testing classification matrices between balanced and unbalanced training distributions for wheelchair transfer ability

Transfer	Unbalanced			Balanced		
	Yes	No	Recall	Yes	No	Recall
Yes	324	9	97.3%	670	150	79.8%
No	132	5	3.6%	90	37	20.2%
Precision	71.1%	35.7%		88.2%	19.7%	
Overall accuracy			70.0%			74.7%