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IMU-Based Approach to Detect Spastic Cerebral Palsy in Infants at Early Stages

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Abstract

INTRODUCTION: Cerebral Palsy (CP) is a non-progressive neurological disorder affecting muscle control in early childhood, leading to permanent alterations in body posture and movement. Early identification is crucial for accurate diagnosis and therapy-based interventions. In recent years, an automated monitoring system has been developed to facilitate the health assessment of infants, enabling early recognition of neurological dysfunctions in high-risk infants. However, the interpretation of these assessments lacks standardization and is subject to examiner bias.
OBJECTIVES: Many infants with CP exhibit increased tonic stretch reflexes due to Upper Motor Neuron Syndrome (UMNS), resulting from motor neuron damage that disrupts muscle signalling.
METHOD: To detect abnormal muscle reactions, our team employed an Inertial Measurement Unit (IMU) sensor, comprising three tri-axial sensors (accelerometer, gyroscope, magnetometer) that capture movement data continuously and unobtrusively. IMU sensors are compact, cost-effective, and have low processing requirements, requiring attachment to the infant's body to measure inter-body part angles. Our team analyzed muscle activity and posture using IMU sensors, collecting tri-axial data from 43 infants in real-time. Additional factors like age, stride length, and leg length were incorporated into the dataset.
RESULTS: Our team has applied various supervised machine learning approaches to predict CP in infants due to the limited dataset size, validating models through k-fold cross-validation. Among the models, Naive Bayes (NB) outperformed Logistic Regression (LR), Decision Tree (DT), Linear Discriminant Analysis (LDA), k-Nearest Neighbors (kNN), and Support Vector Machine (SVM), achieving an accuracy of 88%. CONCLUSION: This research contributes to the early detection and intervention of CP in infants, potentially improving their long-term outcomes.

Keywords: Cerebral Palsy, Spastic Cerebral Palsy, Fidgety Movements, Inertial Measurement Unit, General Movement Assessment

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1. Introduction

As per the World Health Organization (WHO) facts, every year almost forty-one percentage of newborns account for all under-five child fatalities and babies within the first 28 days of life [1]. It is anticipated that approximately fifteen million children are born premature (before 37 weeks of gestation) every year in the world [2]. Preterm neonates with CP, which affects four to twenty percent of them depending on their gestational age, have the most common motor damage [2]. Infants who are born prematurely are at a greater risk of neurological and motor damage. Normally, Lower motor neurons, which are found in the brain stem and spinal cord, are guided by upper motor neurons, which are brain-based nerve cells, to move the muscles. Muscle movements are produced when signals from the upper motor neurons are

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passed on to minimal motor neurons and then from minimal motor neurons to the muscles in the body. These motor neurons are basically the cells that are responsible for controlling all kinds of muscle activities from swallowing to speaking to eating to walking to running. These motor neurons are sometimes damaged by diseases known as Motor Neuron Diseases (MNDs). MNDs are a group of advanced neurological disorders. Gestational age describes the length of the pregnancy. There are more male infants (52.5%) born with CP as compared to female infants (47.5 %) [4].

Brain injury that occurs at or before birth or during the first two years of life is typically the cause of CP. The terms cerebral and palsy relate to the largest portion of the brain, the cerebrum (front of the brain), which is the section of the brain that is affected. Therefore, CP refers to the brain injury's resultant disorder in the brain that affects movement, balance and muscle tone. The strength and tension of the muscles are defined as the muscles' tone. CP is permanent and non-progressive in nature. It is permanent means the core injury to the brain cannot be cured although the treatment might help the CP patient to move better. Also, for a child having CP, intervention programs might be most favorable in very early life as the nervous system is most malleable during that time [6],[7],[8],[9]. Hence, the earliest detection of CP is highly important. On the contrary, CP is challenging to diagnose early. Typically, detection of CP is established by 1 year of child age and even later in case of mild cases [10],[11]. It is especially crucial to identify infants at extreme risk of subsequent motor deficiency at the earliest.

Infants' general movements (GMs), which can vary in sequence, speed, and amplitude, are brought on by a sizable neural generator network that extends from the brain stem to the spine. Long-time assessment of GMs is regarded as a major tool for monitoring infant brain integrity and a decent forecaster for predicting motor compromise which may lead to CP [12]. Typically, GM manifests from the seventh postmenstrual week until three to five months after term [13], as depicted in Fig.2. Due to early diagnosis, relevant intervention programs can be started at an early age with potentially better results.

The General Movements Assessment (GMA) identifies absent or abnormal GMs and depending on the type of GMs' abnormality it can diagnosed the risk of CP with an acuteness of almost 98% [14]. GMA is done with the awake, silent and not crying infant lying on their back (supine position). During GMA, the infant should not have any kind of distraction like toys, pacifiers and parents. In such a situation, the infant is filmed for around 3 to 5 minutes and this video is then analyzed for assessment score by a trained person. Using the GMA method, which is based on films of the infant that are assessed by experienced professionals, requires a lot of time and money.

CP is non-progressive, which means that while the specific symptoms could get worse over the course of an infant's life, the injury won't get worse. In other words, it permanently impairs coordination and movement, but it is not progressive.

Significant motor impairment is more likely in babies born prematurely (before thirty-seven weeks of gestation), with low birth weight (weighing under 1500 g at third trimester), and especially in babies with severely low birth weight (weighing less than 1000 g at the end of 28 weeks of pregnancy [5]. The cerebrum can become damaged during pregnancy, right after delivery, or very early in life, causing CP, or it can develop improperly. The brain can be damaged, or its growth can be disrupted primarily due to:

1). Lack of oxygen to the brain
2). Lack of blood flow to important organs
3). Bleeding in the brain of the baby during pregnancy, around birth or afterwards
4). Seizures within the first month of life or at birth
5). Several genetic disorders
6). Traumatic dementia
7). Premature birth at very less gestational age

Certain infections and viruses such as Rubella, Chickenpox, Herpes, and Zika to name a few, also increase the chances of CP risk if mother suffers with them during pregnancy. Besides that, it also depends on the blood incompatibility of mother and baby or having multiples like twins or triplets. In contrast to traditional classification methods.

1.1 Cerebral Palsy and its Types

Cerebral palsy is fragmented into different categorized based on two factors: 1) the types of movements' issues, 2) body parts being affected. The types of movements' issues in a person having CP depend on how severely a brain injury has impacted the muscle tone. A few signs of CP include shaking hands, weakened muscles, swollen muscles, and insufficient coordination. Impairment of movement brought on by floppy or inflexible limbs and trunk, abnormal posture, uncontrollable motions, shaky walking, abnormal reflexes, or a combination of these, are symptoms of CP.

There are four types of CP as shown in Fig. 1. 1) Spastic Cerebral Palsy, 2) Dyskinetic Cerebral Palsy, 3) Ataxic Cerebral Palsy, and 4) Hypotonic Cerebral Palsy. Spastic cerebral palsy is the most common type of CP. In spastic CP, some simple tasks are more challenging such as walking and picking small objects.

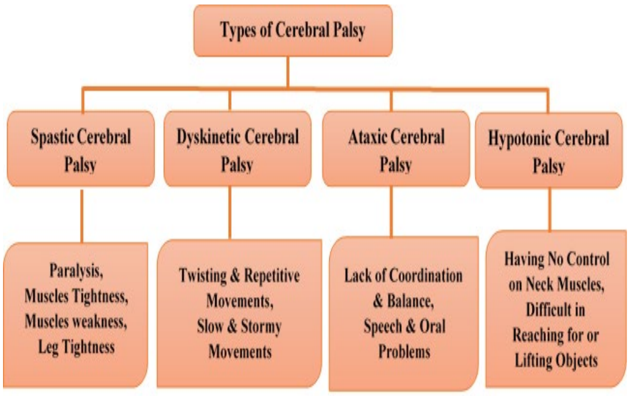

Figure 1. Types of Cerebral Palsy

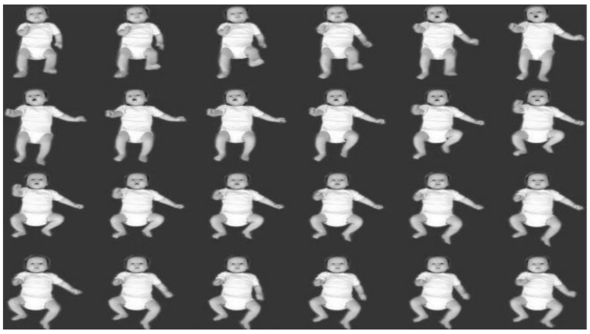

Figure 2. Printed video of a 14-week-old baby with unsteady movements

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To monitor and record the infant's limb movements, digital camera systems (DCS) have been utilized in conjunction with several other coding programs, such as observer coding program. Although DCS is non-invasive, it has drawbacks such as object occlusion, the requirement for intricate digital calibration, the illumination of markers, and cautious zoom adjustments.

Some **Motion Capture Sensors (MCS)** such as Optical Sensor, Electromyography (EMG), Surface Electromyography (sEMG), Accelerometer, Gyroscope, IMU, Infants with spastic cerebral palsy can have their condition detected using EMG, to name a few. Although the accelerometer recorded the infant's spontaneous upper- and lower-acuteness movements, it did not record his or her posture. EMG has been used to record the visual presentation or the electrical activity of muscular tissue. Surface EMG is an electrochemical transducer that detects bio-potentials by using electrodes placed on the skin.

Some other methods like machine learning and deep learning also developed to detect high-risk infants. The machine learning algorithm is one of the best approaches to classify CP children and healthy children. Some machine learning algorithms such as Decision Tree, SVM, Naïve Bayes, and Kernel Fisher Discriminant (KFD) analysis gives high accuracy to classify CP. The second technique is the Deep Learning (DL) algorithm such as multilayer perceptron (MLP), and artificial neural network (ANN) are used to recognize and group the healthy and CP infants. For detection of CP infants, machine-learning algorithms gives high accuracy as compared to deep learning techniques.

The structure of this paper is as follows: Section II provides the interpretation of spastic CP. Section III discusses and compares the broader categories of the available methods to evaluate spastic CP. Section IV describes the process and execution of the task done. Section VI includes results and discussion, and Section VII gives the conclusion.

2. Spastic Cerebral Palsy

Spastic CP influences the cerebral cortex of the cerebrum, a particular segment of the cerebral cortex liable for the arranging and finishing of the deliberate movement. Spastic CP shown in figure 3, is the most widely recognized cerebral paralysis, effecting generally 70-80% of CP cases. Spastic CP is a lasting condition and will influence a person over the lifespan.

Figure 3. Spastic Cerebral Palsy

Movements might be awkward for those with spastic CP because of their stiffened muscles from enlarged muscle tone. Spastic CP is often classified according to the body parts that are impacted:

- Spastic diplegia / diparesis— In this particular kind of muscle rigidity, according to CP, mostly affects the legs and has minimal to no effect on arm movement. People who have spastic diplegia have trouble walking because their legs draw cross his/her knees while facing inward. (a condition known as scissoring).
- Spastic hemiplegia/hemiparesis— In this form of CP, the development problems might affect any one side of the body, with the arm being stiffer than the leg.
- Spastic quadriplegia / quadriparesis— The most severe type of spastic CP, spastic quadriplegia, affects the entire body, including the face, torso, and all upper and lower limbs. Spastic quadriplegia patients typically are unable to walk and frequently have other co-occurring conditions such seizures, epilepsy, intellectual impairment, or difficulties with speech, hearing, or vision.
- Infants with spastic CP have difficulty feeding, interacting, and controlling their growth. Many infants with spastic cerebral palsy walk in an unusual way, as if they were walking on their toes rather on their feet. The following are symptoms of spastic cerebral paralysis:

1. Hypertonia, either one or both sides of the body can suffer from tight muscles.
2. Exaggerated moves.
3. Constrained movement
4. Unusual gait
5. Knees bent in a cross
6. Problem of joint's extension
7. Walking on tiptoes
8. Contractures
9. Abnormal reflexes

3. Diverse Methods for assessing Spastic Cerebral Palsy

The brain damage that produces spastic CP is stable over time, therefore the infant experiences lifelong suffering. To detect spasticity at early stages, there are innumerable techniques that are used by paediatrician to detect high-risk infants as mentioned in figure 4.

Many efforts have been made to collect data that can be analyzed regarding the limbs' inclinations, which is crucial data for CP identification. Figure 5 shows a paediatrician measuring the joint angle manually or using a goniometer. Some of the time paediatricians couldn't quantify the point precisely in a baby which may prompt an inappropriate detection of CP. But these manual techniques do not give accurate angles of the limbs to detect spasticity.

During the 9 weeks to 12 week of foetus' existence are a time of rapid cerebral development. Cerebral development realizes constant modification in the muscle tone. Two important features namely postural reaction of muscle tone and reflexes must be examined for detecting CP. Passive tone and active tone are two main components of the resting posture or attitude. The infant's muscles extend when doctors apply positive pressure to them while they are at rest in a passive position, as seen in figure 6, which denotes passive tone. On the other hand, the active tone is the examination of the infant in active situation, for example, the righting reaction (RR) of the trunk when the child is placed vertically by the paediatrician as shown in figure 7. RR triggers in terms of gravity and space, the movement changes from reclining to standing and rotating. They are important for head raising, rolling, sitting, crawling, creeping, standing, walking, running, and maintaining postural alignment or tone. RR is categorized into two general categories:

1. Keeping the head and trunk in mutual alignment to maintain postural alignment or tone.
2. Aligning the head vertically or uprightly in space in proportion to gravity

Additionally, the wearable sensors have been employed extensively in gesture recognition as a result of improved mobile device processing power, increased software [15] accessibility, and more complex sensors [16] and algorithms [17],[18]. Researchers in [19] proposed a novel IMU-based Modified Tardieu Scale (MTS) which enhances the precision and reliability of the conventional MTS system. In recent years sensor-based techniques have been used along with different machine learning models to detect high-risk infants.

from eight muscles in each subject's leg while they walked forward at a comfortable speed on flat terrain. Using a home-built multi-channel framework composed of 16 sEMG sensors, sEMG signals of leg muscle tissue and raising speed

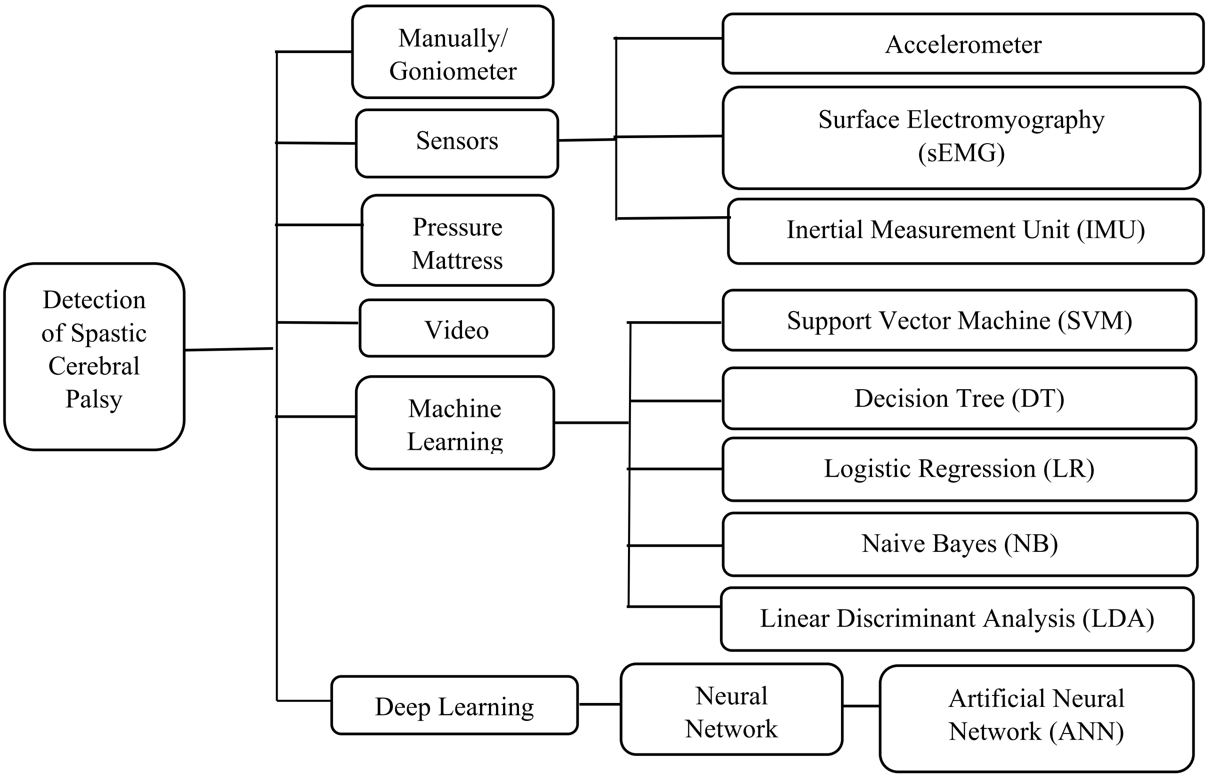

Figure 4. Different Methods for Spastic Cerebral Palsy Detection

Figure 5. Goniometer-Based Angle Measuring

Figure 6. Manually Measurement of angle

In another examination [20], researchers used sEMG signals for assessing the upper and lower extremity anomalies of CP subjects based on the muscle synergy analysis. Muscle synergies, which are determined from EMG data to identify weighted groups of muscles frequently stimulated together, offer a great deal of potential as a metric for motor assessment. Thirty subjects made up a benchmark group, which included a CP group (twelve CP infants), a TD group (eight TD infants) typically developing infants, and an AD group (ten healthy adults). sEMG signals were recorded bilaterally recordings were simultaneously gathered. Muscle synergy analysis showed significant differences between the CP group and the control group, which included AD and TD participants, in terms of decreased synergy number, altered synergy structure, and degraded level of symmetry between the two legs. In children with cerebral palsy, a reduced quantity or symmetry and a variable structure of muscle synergy suggested motor dysfunction.

Figure 7. Righting Reaction with Low

The optoelectronic measurement systems (OMS) such as Qualisys, Vicon, Optotrak, to mention a few are often regarded in literature as the gold standard for motion capture. OMS consists of several high-definition cameras and luminous markers. When the body moves, the luminous markers fixed to certain body parts reflect infrared radiation into the camera lens, where it impacts a light-sensitive lamina and creates a video signal. This way, it estimates a marker's 3D position through time-of-flight triangulation and hence, collects the visual and the depth information of the scene. The following experimental set-up factors affect the systems' accuracy: the positions of the cameras in relation to one another, the distance between the cameras and the markers, their quantity, positions, and types, and their mobility within the capture volume. The examination of an infant's actions can be done impromptu because to simultaneous videotape capture and coding. The development of reach and grip [23], head movement [24], and arm and trunk movement have all been studied using these combinations. Optoelectronic MCS systems have the drawbacks of time-consuming preparation of the measuring device and the newborn with a high number of required markers [25], infant self-occlusion, and missing data as a result of infant's unforeseen movement [26]. The use of marker clusters in such a system has the benefit of reducing system complexity.

A combination of 5 IMUs and 2 pressure-distribution mattresses (CONFOR Mat System, Model 5330, Tekscan, Inc., USA) were used in the research work to measure arm movement and trunk act appraisals, such as trunk place (which comes from the mat), spin (from the IMUs), and associated movements on surface (from both) [27]. Mattresses for pressure distribution typically consist of matrices of sensors with a piezoresistive effect. First, five IMUs are attached to a human copy with genuine infant measurements (shown in figure 8), one on each upper arm, one on each lower arm, and one in the middle. After that, these readings were compared to a healthy infant's movements recorded using the identical pressure mattresses and five IMUs'.

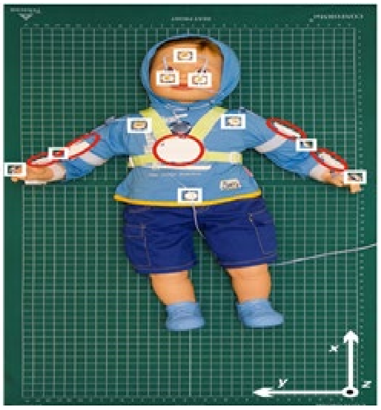

Figure 8. Ten Optotrak markers (one on the baby doll's forehead, one on each cheek, one on the front side of lower abdomen, one on the front side of each shoulder joint, one on the lateral side of each elbow joint, and one on the dorsal side of each hand) are used as references along with IMU sensors attached to the higher limbs and trunk (red ellipses). [5]

A video/IMU hybrid system is also used to estimate newborn development. Twenty newborns between the weeks of 8 and 16 were selected for this framework. Five Shimmer3 sensors were used by the researchers and were affixed to both wrists, both legs, and chest as appeared in figure 9a and 9b. In light of this development estimation, a precision of 84% was accomplished in the classification of fidgety movements in newborn children utilizing SVM. The outcomes in distinguishing fidgety movements are promising on a little dataset yet it should be affirmed on a larger population as well.

Figure 9 (a). Infants with Shimmer Sensors & Colour Patches

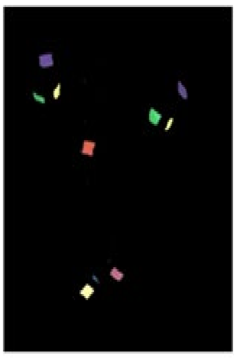

Figure 9 (b). Detection of Colour Patches

An IMU-based posture estimation strategy utilizing extended Kalman filter and kinematic chain modelling has been used in [28]. Three IMU sensors were utilized for pose estimation of hip, kneecap, and heel joint angles during Single Leg Squat (SLS),

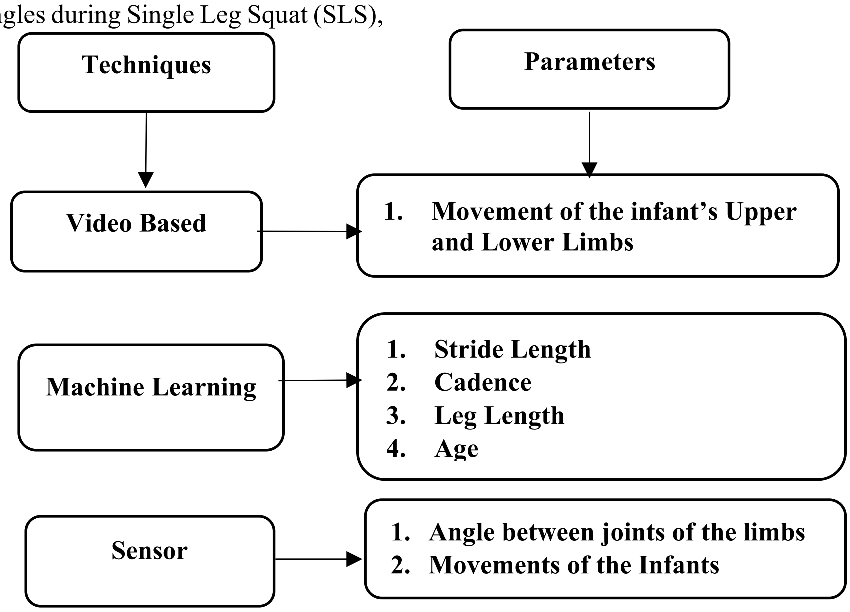

Figure 11. Techniques along with their Parameters used to Detect CP

during clinical development tests. The main advantage of this technology is that it simultaneously offers a tri-axial assessment of the kneecap, lower limb, and pelvic joints. This technology offers accurate position measurements during dynamic coordinated multiple joint movements; as a result, doctors greatly profit from it. Machine learning algorithms have been used in recent years to precisely categorize infants as healthy or high-risk. Researchers in [29], used accelerometers to recognize a specific unconscious motion referred to as Cramped-Synchronized General Movements (CSGM). CSGMs are stiff movements which occur due to the concurrently tensing and relaxing of limb and chest muscles. The lack of the fidgety movements and presence of CSGM predict CP. In this method, data are recorded regarding ten infants that were born between 30 and 43 weeks of pregnancy. A child's upper and lower arms were each equipped with a pair of four independently produced, lightweight wireless accelerometers (two on the wrist and two on the lower thigh). Three Machine Learning algorithms namely pruned DT, SVM, and NB were applied to the features based on the data collected to predict the binary class with a ten-fold cross-validation. As a further benchmark technique researchers predicted the most popular class, "normal". The test's results demonstrate that among all the techniques, choice trees achieve the best precision of 99.46%, followed by SVM's accuracy of 90.46%, and NB's accuracy of 70.43%.

For the detection of CP and right assessment of the therapy effects, the assessment of CP gait patterns is an important factor. Stride length and step length are two important features in gait analysis. Stride length is the separation between subsequent ground contacts of the same heel (known as heel strike or initial contact) while the step length is the distance between two successive heel strike of left and right heel as shown in figure 10. Symptoms including slow walking pace, scissor gait, foot eversion, toe walking, or dragging are all examples of abnormal gait.

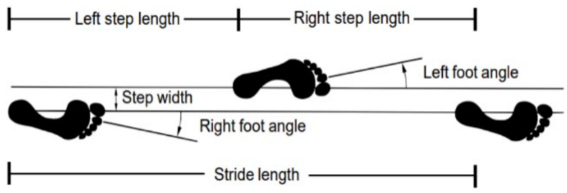

Figure 10. Stride length of the Human

Researcher in [30] have used supervised machine learning algorithm SVM on two input temporal-spatial gait parameters as input i.e cadence, and stride length. In this approach, 156 infants have been taken in which 68 were normal infants and 88 infants suffering CP with spastic diplegia. SVM classifier with ten-fold cross-validation scheme is applied to the dataset. Using SVM, the infants' groups were correctly classified with an accuracy of 83.33%. When the infant's particular leg length and age were adjusted for the walking variables, the accuracy of the SVM classifier increased to 96.80%. The SVM performs 3.21% and 1.93% higher than LDA and MLP based classifier respectively.

Researchers in [31] used various classification algorithms for the gait analysis of CP infants. In this work, a publicly available CP gait dataset with 68 infants in good health and 88 infants having spastic diplegia have been taken with many features including two walking parameters namely stride length and cadence. Various cross-validation testing like holdout, leave-one-out, and ten-fold methods were used for performance comparisons of these classifications' algorithms. Results exhibit that KFD with ten-fold cross-validation provides better accuracy than SVM and outperforms than KNN, DT (or Classification and Regression Trees, CART), and ANN classification methods. Researchers in [33] transforms the assessment into a clustering task. It begins by extracting the infant's joint data using a pose estimation algorithm, segmenting the skeleton sequence into multiple clips with a sliding window technique, and then quantifying infant CP based on the number of cluster classes. The assessment is changed into a task involving clustering by researchers in [33]. Starting with segmenting the skeleton sequence into several clips using a sliding window technique, the program extracts the infant's joint data before estimating infant CP based on the number of cluster classes.

An obvious indication of CP is the absence of fidgety movements (general motions). As per the literature survey, fidgety movements were identified from the infant's limbs motions were recorded by either video cameras or accelerometers. However, both the methods have their own constraints. Video cameras cannot capture the delicate movements because they lack a high temporal resolution while the accelerometers can capture only relative movement due to low spatial resolution.

Specialist have also utilized some advanced sensors, sEMG, a pressure-distribution mattress, and an IMU are a few examples. To measure the angle of joints, these sensors are commonly fastened to the limbs and trunk. In certain research, the data obtained by the aforementioned sensors was subjected to the application of machine learning techniques, including SVM, decision trees, and naive bayes, to name a few. In addition, other characteristics such as (i) stride length (ii) timing (iii)leg dimension (iv) age are also used to predict or characterize CP in infants.

Parameters for the detection of general movements vary according to the techniques used. Typically, sensors are used for measuring the angles of the joints while the machine learning and deep learning approaches mainly focus on four parameters namely, 1) stride length, 2) leg length, 3) cadence and 4) age. Figure 11 shows various techniques and the parameters measured by them while table 1 compares various techniques used till now for the detection of CP infants.

Each one of the studied procedures exclusively has their own particular impediments, for example, the machine learning strategy requires more information for exactness. As a result, these restrictions are overcome and a greater level of accuracy for CP diagnosis in babies is provided by a mix of sensor-based and machine learning methods.

4. Proposed Methodology

Variety of techniques have been used for the measurement of the joint angles ranging from manual measurements to advance sensors to visuals to machine learning algorithms. In the proposed research, our team have worked on a hybrid detection technique inclusive of sensors and machine learning. In the experimental setup, our team have attached nine IMU sensors (two on each forearm and upper arms, two on each lower and upper legs and one on trunk). IMUs were attached to the infants in real scenario in presence of doctors wrapped in a black cloth belt to give a soothing feel to the infants as shown in figure 12. Tri-axial data of the joint angles of the infants' limbs was collected from the accelerometer, gyroscope and magnetometer sensors available inside an IMU sensor as shown in figure 13. Despite the information gathered from the IMU sensor, other parameters namely stride length, timing, and leg dimension of the infants were also measured using the scale.

Figure 12. Nine IMU Sensors Attached on the Infant's Body

5. Implementation and Results

A dataset of 43 infants comprising of 15 healthy infants and 28 spastic CP infants was created. On this dataset, our team have built up machine leaning models using various supervised classification algorithms to classify the dataset into two predefined classes namely, healthy infant, and CP infant.

During the training phase, a model was trained to detect spastic cerebral palsy using the training dataset and then a prediction for the test dataset was done using this trained model. For the model training, our team have employed six machine learning algorithms namely, SVM, NB, LR, kNN, DT, and LDA on the measured dataset. The results were validated using 2-fold cross validation, 3-fold cross validation, and also 4-fold cross validation based on the k-cross validation principle as shown in figure 14.

Our team have taken 2-fold, 3-fold, and 4-fold cross validations. Table 3 provides the accuracies achieved (rounded to 0 decimal places) for LR, DT, kNN, LDA, NB and SVM algorithms. SVM followed by NB outperforms all other algorithms for this particular ratio as shown in figure 15.

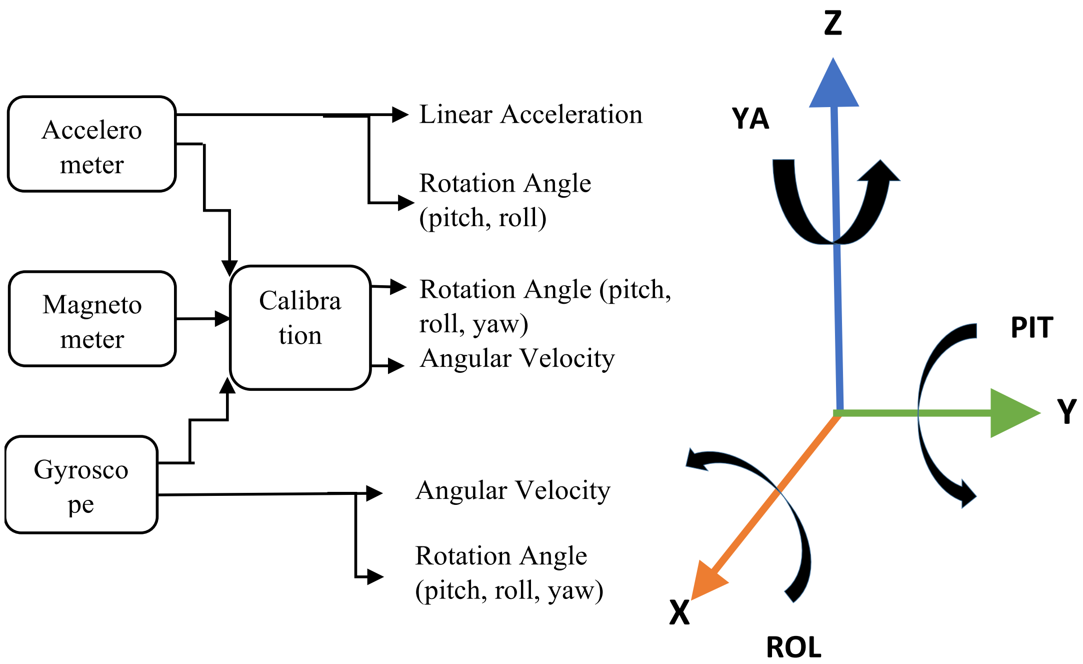

Figure 13. Three Different Types of sensors and Operations of IMU Sensor

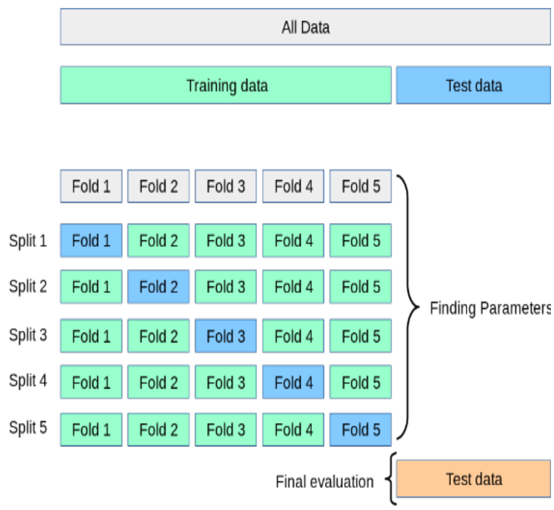

Figure 14. Process of k-fold validation Technique

Table 1. Comparative Analysis of various CP Detection

S. No.	Technique	Measurement	Pros	Cons
1.	Manually/ Goniometer	Joint angle	Identify active & passive tone	No accuracy
2.	Video	Limb Movements	Detecting fidgety movement	Dependency for capturing video
3.	Accelerometer	Limb movements	Recognize the gesture	Measures only horizontal and vertical orientation
4.	sEMG	Limb movements	Easy to understand muscles abnormality Record single muscle activity	Only feasible for single muscle in an individual
5.	Pressure Mattress	Infants' activity level	Simplicity to use	No joint angle measurement
6.	IMU (Accelerometer + Gyroscope)	Joint angle of both limbs (Orientation, and Rotation both)	Accurate angle Low cost Non-invasive	Magnetic field cannot be measured
7.	IMU (Accelerometer + Gyroscope + Magnetometer)	Joint angle of both limbs (Orientation, Rotation, and Magnetic field also)	Accurate angle Low cost Non-invasive Measures 3-dimensional data on each of 3-axis	---
8.	Machine Learning	Stride Length, cadence, leg length, and age	More accurate results	Larger dataset is required

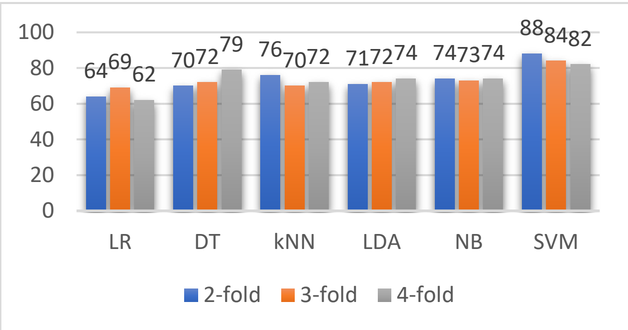

Figure 15. Accuracy of Different Algorithms Using k-fold Techniques

Table 3. Precision of Various ML

k-fold	LR	DT	kNN	LDA	NB	SVM
2-fold	64	70	76	71	74	88
3-fold	69	72	70	72	73	84
4-fold	62	79	72	74	74	82

Algorithms with three different k-cross validations, our team found that SVM provides the best performance in terms of accuracy. An accuracy of 88% is achieved by SVM 2-fold cross validation method which is 14% higher than the NB and 12% higher than kNN. The reason for that is the availability of more data i.e. 80% for training the model in a better way as our team have already a very small dataset due to the non-willingness of the parents for capturing the data on the infants. The results obtained were verified against the ground truth data available with the paediatricians and found correct.

6. Conclusion

Utilizing a machine learning methods, an early identification of CP is preferred. By examining parameters, machine learning methods are utilized to recognize infants with CP like age, cadence, leg length, and stride length. But these parameters can be obtained after the child starts walking.

The IMU-based method is particularly helpful in identifying infants with CP at an early stage. Our team have created a good dataset by attaching nine IMU sensors on upper and lower limbs, and chest of the infant for measuring angles between arms, legs, ankles and other joints. Three-dimensional data from nine tri-axial sensors such as accelerometer, gyroscope, and magnetometer were collected samples per second. This data has been merged with two other factors namely, stride length and leg dimension. Thereafter, different models are being created for the detection of CP infants using machine learning algorithms, SVM, NB, LR, kNN, DT, and LDA models on three training and test dataset ratio of 60:40, 70:30 and 80:20. These models are then being validated using 2-fold, 3-fold, and 4-fold cross validations methods. Results exhibit that with an accuracy of 88%, SVM outperforms all other five algorithms for the ratio 80:20 of training and test dataset respectively. Based on the outcomes, the models' results are also being validated against the ground truth diagnosis done by the paediatricians and found correct.

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