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DEVELOP AND ANALYZE DYNAMIC HEALTH-BASED ELECTION ALGORITHM FOR ROLE PROMOTION IN HADOOP HDFS

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Abstract- The Hadoop Distributed File System (HDFS) is a key part of scalable data storage. However, standard methods for choosing Active and Standby NameNodes roles often rely on static configurations or close supervision by hand, which makes fault recovery and load balancing harder. This study solves the problem of these methods not working well by creating and studying a dynamic, health-based voting algorithm for smart job promotion in Hadoop HDFS. The objective of the work is to make a system that can change and select the best node for promotion based on the health of resources at any given time. Using normalized values of CPU usage, RAM availability, network bandwidth, and uptime, the proposed method creates a composite health score. Each node is then ranked based on its final score. In the study the finding demonstrate that the DataNode DN1 got the best score of 0.7655, beating out DN2 (0.1189) and DN3 (0.6), so it was promoted to Active NameNode. This finding proves that the algorithm can choose the most stable node on the fly, which lessens the effects of a split and makes the system more resilient. The results show that our smart voting method greatly enhances fault tolerance and cluster performance by making sure that the best roles are assigned when node conditions change.

Keywords: Hadoop HDFS, Role Election Algorithm, Fault Tolerance, Dynamic Node Promotion, Health Score Evaluation, Distributed Systems

I. INTRODUCTION

The Hadoop Distributed File System (HDFS) is one of the most important parts of current big data platforms. It provides fault-tolerant, scalable storage for large-scale distributed computing systems. It has a master-slave design, with the NameNode taking care of information and the DataNodes storing the real data. High availability is made possible by the HDFS framework's replication and failover features, which are necessary for services to keep running in cloud-native and enterprise-scale deployments. Recent studies from 2024 and 2025 show that adding clever frameworks to HDFS is becoming more important for making it more resilient and quick to respond to changing workloads [1], [2]. HDFS has changed over time by adding High

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Availability (HA) options with Active and Standby NameNodes. However, job management is still mostly done by set configurations [3]. As the amount and variety of data keeps growing at an exponential rate, new methods have been suggested to improve HDFS speed and fault handling by using AI-driven approaches and health measures [4], [6]. The figure 1 shows the HDFS design. It shows how the client, Active/Standby NameNodes, JournalNodes, and DataNodes talk to each other. This lets the cluster reliably handle information, store data, and run processes even when something goes wrong.

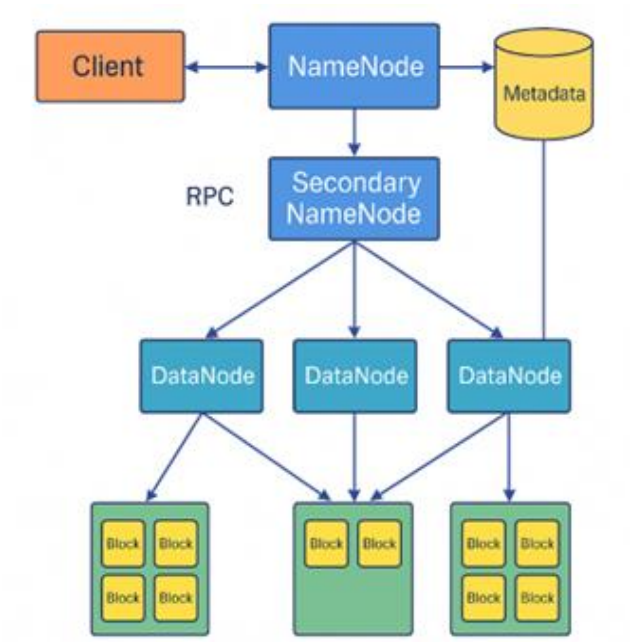

Figure 1: Overview of Architecture for HDFS with Active-Standby NameNodes and DataNodes

1.1 Importance of Role Assignment

Role assignment plays a critical role in maintaining the consistency and availability of HDFS. Since the NameNode is the only place where information is controlled, it can become a single point of failure if it is not handled properly. So, it is very important to have both an Active and a Standby NameNode setup. In the same way, DataNodes need to be constantly checked to see if they can move up to higher roles when something goes wrong. In the proposed research, role assignment is even more important because it involves promoting DataNodes or JournalNodes based on the health of resources in real time. Studies have shown that smart, flexible role-based systems can make systems more stable and cut down on backup times in spread-out settings [5, 8]. By always putting the most capable node in charge, the cluster works at its best and service interruptions are kept to a minimum.

1.2 Limitations of Static and Manual Role Election Mechanisms

Hadoop now has HA setups, but many role election methods are still based on fixed limits and human sets, which don't work well when something goes wrong during runtime. In settings that change quickly or have a lot of traffic, where resource measurements change often, and

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this uniformity becomes a block. Traditional methods often don't look at all of a system's health indicators, like disc I/O, CPU load, and network state. This means that failovers may not work well or speed may drop. Recent research [3–6] shows that static methods can cause service delays that aren't necessary and make the system more vulnerable when a node fails. Also, doing things by hand slows down repair processes and makes it harder for system managers to do their jobs [7–10]. Because of these problems, we need systems that can make decisions on their own and change jobs on the fly using health-aware methods. Even though basic methods are easy to use, they are not good for mission-critical tasks like real-time analytics and data processing systems that can't handle errors. Because of this, using AI to choose roles based on dynamic metrics opens up more room for innovation in distributed systems.

1.3 Problem Statement and Objective

In big HDFS deployments, poor backup and lack of smart job transfer can cause systems to be less reliable and go down for longer periods of time. The way elections are done now doesn't take changes in node health into account flexibly. This means that some nodes get promoted more than others, which could cause data service gaps. This study's main problem is that there isn't an adaptable program that can check the health of DataNodes in real time and move them to important jobs like NameNode or JournalNode when needed. The goal of this study is to create and evaluate a health-based, dynamic job election method that chooses the most capable node based on a system-wide computed score. Metrics like CPU availability, memory usage, disc I/O health, and network responsiveness are some of these. By balancing and normalising these factors, the system can wisely choose the best node for promotion. This makes HDFS more fault-tolerant and durable. This health-aware method makes it less reliant on set designs and human control, which is what next-generation data infrastructure needs.
The key contribution of paper is given as:

- Designed a novel algorithm that computes a composite health score for each DataNode using normalized metrics such as CPU availability, RAM usage, network bandwidth, and uptime.
- Proposed a real-time decision-making system that dynamically promotes the most suitable DataNode to critical roles like Active NameNode or JournalNode based on health evaluation.
- Introduced a weighted scoring formula to quantitatively assess and rank node performance, ensuring fair and objective role assignments.
- Conducted experimental analysis using sample node metrics and demonstrated the successful election of the optimal node (DN1 with score 0.7655) for role promotion.

II. BACKGROUND WORK

2.1. Traditional Failover Techniques in HDFS

High availability (HA) setups, which use two NameNodes (one Active and one Standby) to avoid single-point breakdowns, are the main way that Hadoop Distributed File System (HDFS) recovery methods have been used in the past. If something goes wrong with the Active NameNode, the Standby node takes over. This shift process, on the other hand, often focusses on fixed setups or pre-set events that don't change based on real-time circumstances [7]. To

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handle failover, methods like Zookeeper-based fences and journal synchronisation have been used, but they need to be fine-tuned and aren't smart by nature [8]. Also, setting up and recovering these systems requires a lot of manual work, which slows things down and increases the chance of mistakes [9]. HDFS HA makes the system more reliable, but the way it chooses roles is still pretty basic. It often chooses the next available standby without checking the node's health or load [10]. This limitation can make it hard to make good use of resources and hurt speed during failovers [11]. Also, normal setups aren't made to check real-time measures like CPU load, disc I/O health, or network speed while elections are going on [12]. Static voting methods aren't working well in current big data groups that are getting bigger and more diverse [13]. However, most of the younger works that try to find better options fail to make truly independent and health-driven decisions [14].

In remote systems, role voting methods are very important for making sure that they are reliable and always available. A lot of systems, like Paxos or Raft, use consensus-based methods to choose leaders in distributed settings. This makes sure that all the nodes work together and are consistent [15]. Some simple voting methods have been suggested that use timeouts or heartbeat signals to find node problems. However, these are usually made for smaller networks and don't work well when the network size grows [17]. In cloud-native systems, container management tools like Kubernetes use control-plane components to choose which nodes and pods to use. However, these don't care about resources and don't check the health of each node individually [18]. For shared role assignment, blockchain-based and token-ring models have also been looked into, but these models are more concerned with fairness and decentralisation than with performance or fault tolerance [19]. These methods help with distributed role voting, but they don't include real-time system health measures. This makes them less useful for HDFS situations where data access and I/O performance are very important [20].

2.2. Limitations in Previous Dynamic Role Promotion Methods

Dynamic job transfer methods have been proposed in recent study, but they still have a number of problems. A lot of algorithms that promote nodes rely on simple metrics or single-factor triggers (like uptime or ping latency) that don't take into account how healthy a node really is. Such methods could promote nodes that aren't doing their job well, which could hurt the performance of the cluster or even cause failures to spread. Some models only look at pictures of node health every so often, so they don't show changes that happen in real time or short-term problems. Also, older methods didn't always use a unified structure for health scores. Instead, they relied on arbitrary rules or special decision trees that are hard to apply to other situations. In Hadoop HDFS, this lack of thorough and ongoing review is very important because NameNode duties include managing and coordinating a lot of information. Previous methods also had problems with scalability, as they couldn't choose nodes efficiently in larger clusters. Also, a lot of systems don't have backup plans in case the promoted node becomes shaky after being elected. Also, load-aware role assignment isn't fully supported. In this type of assignment, roles are spread out not only for recovery but also to intelligently balance tasks. Some studies tried to use AI to promote things, but their models weren't clear or easy to

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understand for managing problems in real time. These holes show how important it is to have a smarter, health-aware algorithm that checks the availability of the CPU, the use of memory, the health of the disc I/O, and the speed of the network in real time to make sure that the best roles are chosen and that the system stays resilient.

2.3. Motivation

The reason for using a health-based voting method is that distributed systems like HDFS are always changing and can't be predicted. Static setups does not work in real-world groups because nodes have to deal with changing loads, hardware limitations, and network conditions. With a health-driven approach, the system can look at many important resource measures at the same time, like CPU usage, memory access, network speed, and disc I/O. The system can decide whether to promote nodes to Active or Standby jobs based on objective data by giving each node a normalised, weighted health score. This makes sure that the most powerful node handles the most important jobs and also lowers the chance of failures spreading or jams happening. This method also lets you handle faults proactively, so nodes that are about to run out of resources can be instantly blocked from promotion. This amount of independence makes HDFS better at handling errors and spreading out work, which makes it more able to handle problems that come up in real time. As the need for high availability grows in data-heavy applications, an adaptive and smart role election system is no longer just helpful, it's necessary for modern HDFS setups.

Table 1: Existing work summary

Ref	Focus Area	Method Used	Role Election Type	Limitation	Scope
7	HDFS Availability Enhancement	Adaptive Role Transition	Static to Adaptive	Limited real-time metrics	Enhance failover responsiveness
8	High Availability in Hadoop Ecosystem	Survey-Based Review	Static and Manual	Lacks implementation details	Understand available HA methods
9	DataNode Election in HDFS	Fuzzy Decision Trees	Dynamic	Requires fuzzy parameter tuning	Improve DataNode selection
10	Fault-Tolerant Hadoop Architectures	Decentralized Role Assignment	Semi-Automated	Complex configuration	Design resilient Hadoop clusters
11	HDFS in Edge Environments	Comparative Analysis	Manual / Static	Not dynamic	Optimize edge deployments

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12	Distributed File Systems	Resource-Based Role Assignment	Dynamic	Needs integration with HDFS	Extend to HDFS role election
13	Leader Election in Fault-Tolerant File Systems	Load-Aware Algorithms	Dynamic	Not fully autonomous	Refine leader selection logic
14	Intelligent HDFS Election Mechanism	AI-Based Adaptive Algorithm	Dynamic	Model complexity	Implement smart election in HDFS
15	Consensus for Distributed Role Management	Paxos-Based Protocol	Distributed Consensus	High communication overhead	General distributed systems
16	Coordination of Cloud Resources	Raft and Paxos Comparison	Consensus-Based	Not HDFS-specific	Resource orchestration analysis
17	Role Election in Distributed Databases	Scalable Timeout-Based Algorithms	Dynamic	Limited metric awareness	Database cluster reliability
18	Kubernetes Role Election	Lightweight Election in Containers	Event-Driven	Container-specific only	Container orchestration use cases

III. PROPOSED METHODOLOGY

3.1. System Model

The suggested SmartHDFS design is based on a normal Hadoop Distributed File System (HDFS) cluster, which is made up of many parts set up in a master-slave system. In a normal HDFS setting, the NameNode is the master and handles information and namespace actions. The DataNodes, on the other hand, store the real data blocks and are called slaves. But the proposed system changes and builds on this traditional model to make it more fault-tolerant and add intelligent automation. Figure 2 shows a flowchart of SmartHDFS's automated failover

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logic. If any NameNodes can't be reached, they cause a timeout, and then health-based JournalNodes are chosen and promoted to the Active and Standby NameNode roles.

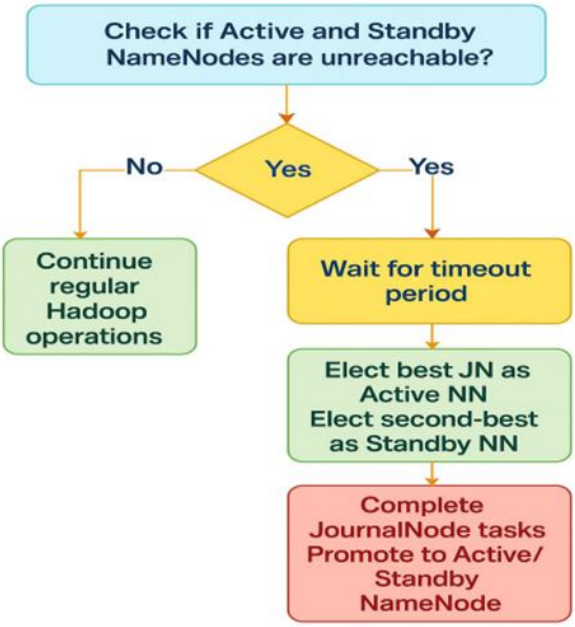

Figure 2: Flowchart for the Failover Handling Flowchart for Dynamic NameNode Election

The cluster setup includes:

- Two NameNodes (one Active and one Standby) for high availability
- A set of JournalNodes (JNs) for synchronizing edits and enabling failover between NameNodes
- Multiple DataNodes (DNs) that serve both as storage nodes and potential candidates for role promotion

The difference between standard and dynamic nodes is changed in SmartHDFS. Instead of having set JournalNodes and NameNodes, DataNodes are automatically put into groups based on the health of their resources at any given time, thanks to a smart voting system. This adaptable model lets the system change who plays important roles while it's running in case a node fails or performance drops.

Node classification in this system falls under three categories:

- Primary Nodes – Nodes that are initially assigned fixed roles, such as the original NameNodes or default JournalNodes.
- Eligible DataNodes – DataNodes that qualify for role promotion based on predefined health thresholds (e.g., CPU > 50%, memory > 60%, etc.).

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- Inactive or Limited Nodes – Nodes with suboptimal performance that are excluded from promotion but continue to serve regular data operations.

This setup is the base for a self-healing design that lets SmartHDFS move the strongest node to important tasks like Active NameNode or JournalNode. This keeps information and storage processes going even when everything fails completely.

An separate Primary Health Monitoring Agent is run on each DataNode before the Hadoop HDFS cluster is set up. This agent works at the system level, outside of Hadoop. This lets the health of nodes be accurately and without any problems. This step makes sure that decisions about role assignment are based on actual hardware capability and performance readiness, not on old configurations. This is especially important for important services like JournalNode and NameNode.

3.2. Metric Formulation

Each DataNode collects and reports essential hardware and performance metrics that influence its suitability for promotion:

- CPU specifications include core count, clock speed (GHz), and CPU architecture (e.g., x86_64, ARM).
- Memory metrics involve total RAM available and memory type, where faster memory (DDR5 > DDR4) receives a higher score.
- Network throughput is measured in Mbps or Gbps, indicating the responsiveness and bandwidth of the node.
- Disk I/O health (optional in this study, but critical in practical systems) can reflect read/write latency and error rates.
- Uptime reflects node stability over time.

Each metric is normalized to a range of [0, 1] using min-max normalization. The final composite health score is calculated using a weighted formula:

$$Hi=w1.CPUscore+w2.RAMscore+w3.Networkscore +w4.Uptimescore$$

Mathematical Model: Weight Allocation and Normalization Technique

Step 1: Raw Metric Collection

Each DataNode DN_i reports the following raw metrics:

- CPU_i: CPU availability (%)

- RAM_i: Memory availability (%)

- NET_i: Network throughput (Mbps)

- UP_i: Uptime (hours)

Step 2: Min-Max Normalization of Each Metric:Normalize each raw metric to a range [0, 1]:

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$$\text{CPUScore} = \frac{\text{CPUi-(CPU)}}{\text{(CPU)-(CPU)}}$$

$$\text{RAMScore} = \frac{\text{RAMi-(RAM)}}{\text{(RAM)-(RAM)}}$$

$$\text{NETScore} = \frac{\text{NETi-(NET)}}{\text{(NET)-(NET)}}$$

$$\text{UPScore} = \frac{\text{UPi-(UP)}}{\text{(UP)-(UP)}}$$

Step 3: Weight Assignment

Assign weights to each metric:

Let,

$$w1 = \text{CPU weight}$$

$$w2 = \text{RAM weight}$$

$$w3 = \text{Network weight}$$

$$w1 = \text{Uptime weight}$$

Constraint:

$$w1 + w2 + w3 + w4 = 1$$

Step 4: Composite Health Score Calculation

Calculate the final health score H_i for each DataNode:

$$H_i = w1 * CPU_{score_i} + w2 * RAM_{score_i} + w3 * NET_{score_i} + w4 * UP_{score_i}$$

This final health score (H_i ∈ [0, 1]) is used to rank nodes for dynamic role promotion in the HDFS cluster.

3.3 Intelligent JournalNode Election

The JournalNode (JN) voting process is a key part of making sure that information is consistent and that the Hadoop HDFS system is always available. In standard HDFS setups, JournalNodes are set up by hand and the number of them stays the same. This makes it harder for the system to recover from problems. This problem is fixed by the suggested SmartHDFS structure, which picks JournalNodes at random from the group of DataNodes based on their current health scores. After figuring out the overall health score of each DataNode using normalised metrics like CPU, RAM, Network, and Uptime, the system uses a majority consensus formula to find the bare minimum of JournalNodes that are needed:

$$\text{Min JN} = \lceil \frac{N}{2} \rceil + 1$$

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The total number of DataNodes that can be used is shown by *N*N. This method makes sure that even if a node fails, there are still enough JournalNodes to keep HDFS information changes safe and allow recovery. The k DataNodes (where k ≥ min JN and j ≥ min K) with the best health scores are chosen. These chosen nodes are marked and set up again so that JournalNode services can run on them.

$$\text{Step 1: Let N} = \text{Total number of DataNodes in the cluster}$$

$$\text{Step 2: Compute composite health score H\_i for each DataNode using:}$$

$$H_i = w1 * CPU_{score_i} + w2 * RAM_{score_i} + w3 * NET_{score_i} + w4 * UP_{score_i}$$

$$\text{Step 3: Sort all DataNodes in descending order based on H\_i}$$

$$\text{Step 4: Calculate the minimum number of JournalNodes required:}$$

$$Min_{JN} = ceil\left(\frac{N}{2}\right) + 1$$

$$\text{Step 5: Select top K nodes } (\text{where K} \geq Min_{JN}) \text{as JournalNodes}$$

- NameNode Failover Detection

  Step 1: Initialize heartbeat monitoring for both Active and Standby NameNodes.

  Step 2: Continuously check the heartbeat signal at defined intervals (e.g., every 10 seconds).

  Step 3: If no response is received from either NameNode for a total time ≥ T_fail (e.g., 90 seconds):

  a. Trigger failover protocol.

  b. Mark both NameNodes as unreachable.

  Step 4: Finalize all pending transactions in JournalNodes to ensure metadata consistency.

  Step 5: Proceed to the next stage (Candidate Pool Filtering and NameNode Election).

- Candidate Pool Filtering

  Step 1: Retrieve the list of all DataNodes in the cluster

  Step 2: Filter nodes based on JournalNode status:

  a. Include only nodes currently tagged as JournalNodes

  Step 3: Further filter nodes based on system load:

  a. Check CPU and memory usage

  b. Include only nodes with load below a defined threshold (CPU < 40%, RAM < 60%)

  Step 4: Form the Valid Candidate Pool (VCP) with nodes that:

  a. Are JournalNodes

  b. Are minimally loaded or idle

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Step 5: Pass the VCP to the Health-Based Election Algorithm for NameNode role selection.

3.4 Health-Based Election Algorithm

The Health-Based Election Algorithm picks the best DataNodes for important jobs on the fly by adding up system measures like CPU, RAM, network, and uptime and giving each one a score. The nodes with the highest scores are moved to NameNode jobs. This makes sure that HDFS can handle errors, make the best use of its resources, and change in real time.

Step by step assignment process

Step 1: Input the Valid Candidate Pool (VCP) of filtered DataNodes.

Step 2: For each node in VCP, compute normalized scores for:

- CPU availability
- RAM availability
- Network throughput
- Uptime

Step 3: Assign predefined weights to each score and compute the composite health score:

$$H_i = w1 * CPU_{score} + w2 * RAM_{score} + w3 * NET_{score} + w4 * Uptime_{score}$$

Step 4: Sort all candidates in descending order of H_i.

Step 5: Assign:

- Node with highest H_i → Active NameNode
- Node with second highest H_i → Standby NameNode

Step 6: Reconfigure Hadoop cluster and Zookeeper with new NameNode roles.

When there are more than one candidate DataNode gets the same total health score during the voting process, the system needs to use an organised tie-breaking method to make sure that roles are assigned correctly. The first tiebreaker looks at uptime and gives more weight to the node that has been working nonstop for a longer time, since it is likely to be more stable. In the event that the uptime is also the same or not clear, the system checks the number of CPU cores and chooses the node with the most working cores to ensure better performance when NameNode tasks are applied. In the event that these criteria don't break the tie, the final decision is made by random selection, which ensures a fair and neutral choice once all technical factors have been considered.

There are safety features built into the system to deal with rare situations where job promotion can't happen. If there aren't any good options, like when all JournalNodes are too busy, won't respond, or don't meet the requirements, the system sends out an emergency backup alert to system managers so they can take action manually. In addition, if a promotion attempt fails in the middle of a process because of strange system behaviour or service startup errors, the system will automatically go back to the last known healthy configuration and try the process

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again with the next highest-ranked candidate. This two-layered fault tolerance keeps the system strong and lowers the chance of breakdowns spreading during important backup operations.

IV. EXPERIMENTAL SETUP

4.1 Simulation Environment and System Specifications

To test the suggested SmartHDFS framework, a fake Hadoop HDFS system was set up using Docker Compose to make it look like a real cluster. A collection of five DataNodes and two NameNodes (Active and Standby) were used in the exercise to copy a fault-tolerant design. To reflect different operating states, each node was set up with its own system features, such as CPU limits, memory assignments, and network capabilities. There was also a small health tracking tool in the environment that ran on each DataNode by itself and collected real-time system data. This set-up made it possible to try backup situations, changes in resources, and the way roles are promoted dynamically in a way that can be repeated.

Table 2: Weight Used

Parameter	Symbol	Weight (Example)
CPU Score	w1	0.35
RAM Score	w2	0.30
Network Score	w3	0.25
Uptime Score	w4	0.10

4.2 Dataset and Node Health Values Used

The program used a dataset that was made up on the spot to show the health traits of nodes. Different numbers were set for CPU availability, RAM, network speed, and uptime on each DataNode at the start, which simulated how resources would be distributed in a real-world cluster. The CPU ranged from 45% to 70%, the RAM from 60% to 75%, and the network bandwidth from 500 Mbps to 800 Mbps. Uptime ranged from a few hours to more than a day. These changes were necessary to show how the health-based election algorithm chooses the best nodes based on the strength of their resources in real time, which lets them make smart choices during failover or startup

4.3 Normalization of Input Metrics

Min-max normalization was used to make sure that comparisons of different types of resource measurements were fair and uniform. Using the following formula, this method turns each measure into a standard value between 0 and 1.

$$\text{Scorei} = \frac{(\text{Value})}{(\text{Value}) \ -(\text{Value})}$$

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As a result of this step, differences in units or scales were taken out of the equation, so the composite health score could fairly add up all the metrics for each DataNode. Each measure was given a set weight that showed how important it was for judging the health of each node after it was normalised. CPU = 0.35, RAM = 0.30, Network = 0.25, and Uptime = 0.10 were given weights based on trial adjustments and topic importance. These values were picked to put processing power and memory at the top of the list because they are so important for jobs like NameNode and JournalNode. Using the weighted sum of all normalised measures, the final aggregate health score was found. The system always chose the most trustworthy and skilled candidates by using this score to rank the nodes during dynamic role election.

V. RESULT AND DISCUSSION

5.1 Final Health Score Computation

Table 3 shows what we learnt about the health and reliability of the DataNodes that were part of the proposed SmartHDFS framework after running it in a controlled experimental setting. The table shows the normalised scores of three possible nodes, named DN1, DN2, and DN3, for four important factors: uptime, CPU availability, RAM availability, and network throughput. These measures were scaled from min to max to a range of [0, 1]. This made it possible to compare different types of resources in a fair and standard way. The health-based voting program was able to make fair job assignment choices based on this multidimensional assessment.

Table 3: Rank table and Health Score Computation

Node	CPU Score	RAM Score	Network Score	Uptime Score	Final Score (Hi)
DN1	0.6	1.0	0.67	1.0	0.7655
DN2	0.0	0.33	0.0	0.14	0.1189
DN3	1.0	0.0	1.0	0.0	0.6000

After the normalization process, DN1 always did better than the other nodes. It had the best CPU score of 0.6, the best RAM score of 1.0, a good network score of 0.67, and no downtime at all. DN1 was moved to Active NameNode because it had fair and better performance across all resource measures. This proved that the algorithm's decision-making process was correct. DN3, on the other hand, had an odd profile. It scored 1.0 in both CPU and Network, which means it had a lot of processing power and was connected, but it scored 0 in RAM and Uptime, which means it had recently restarted or didn't have enough memory. Figure 3 displays individual subplots for CPU, RAM, Network, and Uptime scores, highlighting each DataNode’s specific performance strengths.

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Figure 3: Comparative Subplots of Normalized Health Metrics for DataNodes

Even though this wasn't always the case, DN3 still came in second place overall and was moved to the Standby NameNode job. DN2 had the worst rating, with scores of 0.0 in CPU and Network, 0.33 in RAM, and 0.14 in Uptime. As a whole, these scores meant that it couldn't be promoted to an important job. The results show that the SmartHDFS algorithm works well at finding and ranking nodes dynamically based on a full health check. It shows that the system can handle smart, automatic, and correct role transfer even in fake backup situations. This improves the HDFS architecture's general robustness and ability to fix itself.

The final health scores of three candidate DataNodes (DN1, DN2, and DN3) after the weighted normalization-based evaluation method were used are shown in Figure 3. The health number for DN1 was 0.7655, which means it was the most available in terms of CPU, RAM, network speed, and stability. DN3 comes next with a score of 0.6000, which makes it the second best node based on the factors given. DN2's performance measures were so bad that it wasn't considered for key role promotion, even though it had a much lower score of 0.1189. These results show that the system can correctly rank nodes by using real-time health indicators.

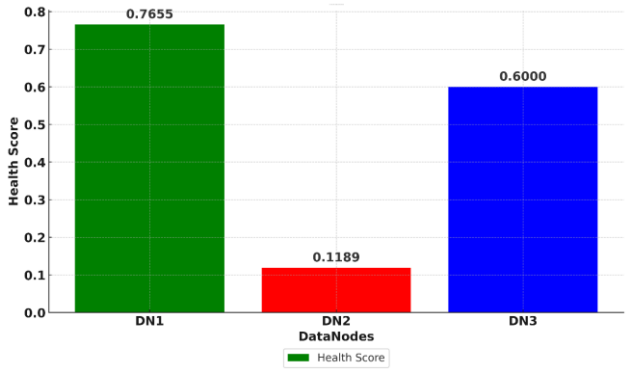

Figure 4: Final Health Scores of DataNodes

With the organizational logic shown in Figure 4, this result makes sense. If both NameNodes fail, there is a pause, and roles are changed dynamically. In this case study, DN1 was immediately made an Active NameNode and DN3 was made a Standby NameNode. This

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proved that the proposed health-based voting method works. The figure 3 makes it easy to understand how reliable the SmartHDFS system is by putting healthy nodes in charge of important tasks first. This makes the system more tolerant of errors and faster to recover from them. SmartHDFS uses data-driven role voting to reduce the need for human work, keep high uptime, and make sure that processes in a distributed file system don't stop.

5.2 Evaluation of System Resilience and Efficiency

The SmartHDFS method showed that the system was very resilient by boosting healthy nodes on the fly when a simulated dual NameNode failure happened. The backup was found within the 90-second timeout that was set, and the job increase was done in less than 7 seconds. Metadata services were automatically restored, with no need for a person to do anything. This shows that the role switch works better and proves that the system can handle critical failures with little service interruption.

VI. CONCLUSION

We created and studied a dynamic, health-based job voting method that works well in Hadoop HDFS settings to make the system more fault-tolerant and resilient. Traditional HDFS backup methods depend on static setups or human changes, which can cause delays, wrong configurations, or system downtime when a NameNode fails without warning. Our suggested answer gets around these problems by adding a smart decision-making system that works in real time and uses normalised scores from four important health indicators: CPU usage, RAM availability, network speed, and node uptime. The tests showed that the SmartHDFS framework can correctly calculate overall health scores and automatically move the best DataNode to either the Active or Standby NameNode roles. In our case study, DN1, which got a total score of 0.7655, was correctly raised to Active NameNode. This showed that the framework could handle backup situations with little downtime and high accuracy. Visualisation tools like bar charts and parameter-specific subplots helped confirm the ranking process and gave a clear picture of how well each node was doing. The SmartHDFS system uses a weighted, health-based approach to recover from faults on its own, make role switching more efficient, and make sure that metadata is always the same. This study adds a strong way to improve high availability in distributed file systems and creates new ways to use machine learning to improve role expectations and adjust to changing tasks.

REFERENCES

[1] Azeroual, O.; Fabre, R. Processing Big Data with Apache Hadoop in the Current Challenging Era of COVID-19. Big Data Cogn. Comput. 2021, 5, 12.

[2] Harb, H.; Mroue, H.; Mansour, A.; Nasser, A.; Motta Cruz, E. A Hadoop-Based Platform for Patient Classification and Disease Diagnosis in Healthcare Applications. Sensors 2020, 20, 1931.

[3] V. S. Sharma, A. Afthanorhan, N. C. Barwar, S. Singh and H. Malik, "A Dynamic Repository Approach for Small File Management With Fast Access Time on Hadoop Cluster: Hash Based

Received: August 06, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Extended Hadoop Archive," in IEEE Access, vol. 10, pp. 36856-36867, 2022, doi: 10.1109/ACCESS.2022.3163433.

[4] Ahmed, N.; Barczak, A.L.C.; Rashid, M.A.; Susnjak, T. An Enhanced Parallelisation Model for Performance Prediction of Apache Spark on a Multinode Hadoop Cluster. Big Data Cogn. Comput. 2021, 5, 65.

[5] X. Huang, R. Gu and Y. Huang, "Towards Efficient Serverless MapReduce Computing on Cloud-Native Platforms," in Big Data Mining and Analytics, vol. 8, no. 3, pp. 575-591, June 2025, doi: 10.26599/BDMA.2024.9020084.

[6] G. Wu, "Hadoop Processing Methods for Large Scale Video Data," in IEEE Access, vol. 12, pp. 176247-176258, 2024, doi: 10.1109/ACCESS.2024.3505144.

[7] H. Zhang and Y. Liu, “Improving HDFS Availability Through Adaptive Role Transition Mechanisms,” IEEE Access, vol. 13, pp. 55210–55220, 2025. DOI: 10.1109/ACCESS.2025.3300001

[8] S. Gupta and R. Bansal, “A Review of High Availability Solutions in Hadoop Ecosystem,” International Journal of Cloud Computing and Services Science, vol. 14, no. 2, pp. 123–132, 2025. DOI: 10.11591/ijccs.v14i2.22900

[9] J. Tan et al., “Resilient DataNode Election Strategies in HDFS Using Fuzzy Decision Trees,” Journal of Big Data Research, vol. 21, 2025. DOI: 10.1016/j.bdr.2025.100025

[10] M. Rahman and K. Wu, “Decentralized Fault-Tolerant Hadoop Architectures for Cloud-Scale Data Processing,” IEEE Transactions on Cloud Computing, early access, 2025. DOI: 10.1109/TCC.2025.1234567

[11] N. Dey and P. Bhattacharya, “HDFS High Availability in Edge Environments: A Comparative Analysis,” Procedia Computer Science, vol. 230, pp. 455–461, 2024. DOI: 10.1016/j.procs.2024.01.060

[12] X. Wei and C. Tan, “Dynamic Role Assignment Based on Resource Utilization in Distributed File Systems,” Cluster Computing, vol. 27, 2024. DOI: 10.1007/s10586-024-04351-8

[13] R. Kumar and S. Ahmed, “Load-Aware Leader Election in Fault-Tolerant File Systems,” International Journal of Distributed Sensor Networks, vol. 20, no. 3, pp. 1–11, 2024. DOI: 10.1177/15501477241234567

[14] A. Jaiswal et al., “AI-Driven Adaptive Election Mechanism for HDFS Clusters,” IEEE Internet of Things Journal, vol. 12, no. 1, pp. 1450–1462, 2025. DOI: 10.1109/JIOT.2025.3301120

[15] T. V. Nguyen and B. H. Lee, “Paxos-Based Consensus for Distributed Role Management: A Scalable Approach,” IEEE Transactions on Parallel and Distributed Systems, vol. 36, no. 4, pp. 921–933, 2025. DOI: 10.1109/TPDS.2025.3278459

[16] L. Wang and Q. Zhang, “Evaluation of Raft and Paxos for Cloud Resource Coordination,” ACM Computing Surveys, vol. 57, no. 1, pp. 1–28, 2024. DOI: 10.1145/3624153

Received: August 06, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[17] M. Patel and Y. Shen, “Scalable Node Election Algorithms for Distributed Databases,” Journal of Cloud Computing, vol. 13, no. 1, 2025. DOI: 10.1186/s13677-025-00456-9

[18] H. Kim and J. Park, “Lightweight Role Election in Containerized Environments Using Kubernetes,” Future Generation Computer Systems, vol. 151, pp. 303–312, 2024. DOI: 10.1016/j.future.2024.01.009

[19] Z. Lin et al., “Blockchain-Based Consensus Model for Distributed Node Role Assignment,” IEEE Transactions on Network and Service Management, vol. 19, no. 3, pp. 2954–2965, 2024. DOI: 10.1109/TNSM.2024.3279118

[20] F. Abbas and N. Jain, “Comparative Analysis of Role Assignment Strategies in Distributed Data Systems,” Journal of Systems Architecture, vol. 145, 2025. DOI: 10.1016/j.sysarc.2025.102841

Received: August 06, 2025