

Heat Work: Choreography as an Ecological Enquiry of Machine Learning and Extractivism

Samir Bhowmik*, Minh Anh Nguyen*, Lydia Touliatou*, Alison Powell¹, Vishnu Vardhani Rajan²

**Joint First Authors – University of the Arts Helsinki*

1. London School of Economics; 2. Artist and Performer

Abstract

Artificial Intelligence (AI) has the potential to both disrupt and transform the performing arts. However, the use of Machine Learning (ML) algorithms in choreography risks leading to a reductive and opaque formalization of choreographic decisions, often disregarding energy consumption and environmental impact. This article explores choreography as a method for examining the energetic materialities of ML and extractivism. Through *Heat Work*, a performance project, it investigates the energy and heat generated by movement data derived from tribal dances within an extraction zone. The methodology includes motion capture, data classification, and the application of a supervised ML model, with a focus on implementing a sustainable approach to choreography with AI. By examining the project's ecological dependencies for choreographic decision-making, the article proposes a sustainable and ethical avenue of research at the intersection of AI, extractivism and performance.

Keywords: choreography, dance, machine learning, energy, extractivism, ethics

1. Introduction: Choreography, AI and Extractivism

Today, choreography with robots and AI in dance and theater has emerged as the latest frontier of performing arts. Choreographers have been experimenting with robots and ML in dance and performance productions. Notable works such as Wayne McGregor's *Living Archive: An AI Performance Experiment* (2019) and *No one is an Island* (2020), Catie Cuan's *OUTPUT* (2020) and Pontus Lidberg's *Centaur* (2020) expand the scope of robotics and AI in understanding, shaping, and predicting performance movements (McGregor 2019, 2020; Cuan 2020, 2021; Lidberg 2020). For example, Google Arts and Culture has collaborated extensively with McGregor to build an online interactive atlas of a half-million digitized movements drawn from his repertory (Girschig 2019). These emerging works have given rise to a genre of so-called "intelligent" performance with significant potential to transform the performing arts. These AI and automation-driven aesthetic works focus primarily on Western performative traditions for generating training data. Additionally, the emphasis is on mapping of performance movements onto locomotive capabilities of industrial robots. Moreover, no publicly available information is available regarding these choreographic works' energy and resource use or research and documentation about their sustainability. This lack of transparency raises concerns about the narrow focus of current choreographic experimentation with AI, particularly regarding its environmental implications.

Undoubtedly "intelligent" performance practices with AI trigger a vast matrix of black-boxed infrastructures and energies. This is similar to an interaction with an AI system where "interlaced chains of resource extraction, human labor and algorithmic processing work across networks of

mining, logistics, distribution, processing, prediction and optimization.” (Crawford & Joler 2019). For instance, Lidberg’s AI-choreographic work *Centaur* raises questions of resource-use, since it involves using an AI model that is fed information from myriad sources ranging from planetary movements to the structure and semiotics of Greek tragedy (Curtis 2020). What is the distributed infrastructure of McGregor’s Living Archive or the embodied energy of Cuan’s robot performances? (Cuan 2021)

Despite innovation in computing, AI methods now require training in ever larger models on sprawling data sets. “Building models for natural language processing and computer vision is enormously energy hungry, and the competition to produce faster and more efficient models has driven computationally greedy methods that expand AI’s carbon footprint” (Crawford 2022, 15; 23-51). An MIT Review (2019) found that training a single AI model can emit as much carbon as five cars in their lifetimes. ML and especially Neural Network (NN) model training requires a tremendous amount of energy and Cloud computing infrastructures (Hao 2019). It is also well known the industrial robots favored in these performances require significant amounts of energy and material resources in their construction and operation (Ystgaard et al. 2012). The approach is computationally energy intensive. As a result, performance practices with ML and AI are inherently unsustainable, causing resource-depletion and have environmental implications.

According to Kate Crawford (2021), “Mining is where we see the extractive politics of AI at their most literal. The tech sector’s demand for rare earth minerals, oil, and coal is vast, but the true costs of this extraction is never borne by the industry itself.” Usually, extraction for technology is conducted out of sight in distant lands such as in the Lithium Triangle (Bolivia, Argentina, Chile), Congo, Inner Mongolia, Indonesia, aboriginal lands in Australia, Lapland and so on. Thus, the biggest impact of AI is felt in the Global South. These are places where there is least environmental regulations and labor laws, and where we find “the repressed stories of acid bleached rivers and decimated landscapes and the extinction of plant and animal species that were once vital to the local ecology” (Crawford 2021, 23-51). Mineral-rich landscapes and indigenous populations become casualties in the battle with knowledge and resources-for-technology extractivism. Extraction of key minerals and metals sustain technologies for AI leave in its wake deforestation and toxic tailings ponds. The largest and most risky tailings dams worldwide are in medium- to low- income countries, places already marked by high levels of social inequality, weak governance, and systemic corruption. In multiple locations throughout the world, “[they] actualize colonial regimes of power and violence, cementing over all kinds of local life projects, especially the ones already affected by multiple other forms of precariousness.” (Ureta and Flores 2022)

One of these locations (a focus area in this article) is the Jharkhand tribal zone in Eastern India. Home to Scheduled Tribes who comprise almost half of the population, Jharkhand is also a vast extraction zone. It accounts for more than 40 percent of the entire mineral resources of India, and yet a substantial amount of its inhabitants is below the poverty line. These resources include iron ore, copper, coal, mica, bauxite, graphite, limestone, and uranium, many of which are vital to power generation, electrification, and technological infrastructures. However, “mining activities, while ostensibly contributing to economic betterment, often result in the displacement and disenfranchisement of indigenous communities. The socio-cultural fabric of these tribal groups, intricately interwoven with their land and natural resources, is subjected to a perturbing disarray.” (Mukherjee 2023, 296) (Sharma 2005). Jharkhand also has vast forests and national parks, many of which are affected by encroaching mining activities and subsequent deforestation

and environmental damage. “The extraction processes, coupled with inadequate mitigation measures, result in habitat degradation and loss, imperiling the biodiversity of the region.” For example, “the uncontrolled mining activities in *Saranda* Valley have led to the degradation of wildlife habitats and disrupted the traditional migration routes of elephants. (Mukherjee 2023, 297)

Within this extraction zone, the Santhals are the largest Scheduled Tribe in Jharkhand who have been constantly oppressed and dispossessed of their land and property throughout their existence. Even today they are subjected to poverty and exploitation, including confiscation of their lands and steady diminishing of their culture. The tribal populations are “heavily reliant on the forest for their livelihoods, face the loss of resources and disruptions in agricultural endeavors due to the alteration of hydrological dynamics. (Mukherjee 2023, 297) Despite the hardships and adversity, Santhals have maintained a strong cultural identity through their arts and crafts such as puppetry and painting, including a wide variety of dances performed at festivals throughout the year. Many of these dances are related to the weather and nature, and thus offer movements inter-linked with extractivism and the environment. In Jharkhand, it is the performance of songs with drumming and collective dance, non-segregated by gender, that most clearly and publicly marks a group as “tribal,” or *adivasi*. (Babiracki 2000, 37). Here, “music and dance together mark various levels of the environment and geographical identities uniting individual lives with the seasonal and the ritual” (Babiracki 2000, 44).

2. Choreography as a Thermal and Energetic Enquiry of Extractivism

Environment and temperature have been key ingredients in tribal lands. Especially, the thermal seeps into every aspect of tribal culture starting from seasonal farming to food preparation in communal hearths to seeking coal in extraction zones. Tribal bodies are linked to their surroundings by the regulation of temperature that is embedded not only in physiological functions but are also as an embodied record of the environment. Much of this remains to be documented properly. According to Starosieslki (2016), “the study of thermocultures, the modes by which temperature is managed and organized in embodied and culturally specific ways, has not been fully accounted for in geological history and technological histories of heating and cooling.” The extractive nature of AI is similarly only visible at the geological level, i.e. mining where thermal manipulation is critical to the transformation of the earth’s raw materials into technologies [media] and to maintain those materials as media. (Starosielski 2016). In our case, we believe intelligent performance with AI is also an ambiguous ground where Extractivism, energy and thermocultures come together but also remain invisible or diluted. Thus, the study of thermality and energy in choreography with AI offers an opening, a way to enquire into both AI methods and extractivism. Studying tribal dances from an extraction zone foregrounds the aspect of heat and energy as entangled with human bodies and AI, that also acts as a critique of extractivism. As Lerner (2022) suggests: “The choreographic body might advance environmental work in ways that foreground how the performing body exposes environmental infrastructures that are occluded from view.”

In this article, we examine *Heat Work*, a choreographic project with the simulation of Santhali dances and ML. We explore whether choreography with ML could offer us a novel methodology of negotiation with heat and energy with regards the resource-use of ML. The aim is to understand the underlying patterns of dance vis-a-vis energy use and possibly generate predictive choreography of movements that diminish the energy footprints and resource-use. As such, the project involves generating a score or list of actions in a performance space, each informed by the heat production of the captured movements. *Heat Work* is composed of three stages: motion capture and data classification of pre-selected dance movements, construction of a ML model, and application of the ML model on the gathered datasets from which predictive routines are generated. The new choreography of routines as ML outputs are guided by our parameters of low energy use and heat, and thus offer a choreographic prototype for further research. As a novel methodology, this choreography becomes a thermal and ecological enquiry into ML and extractivism.

Our approach represents a critical departure from conventional AI applications in dance eschewing popular techniques and virtuosity often seen in contemporary choreographic works, where AI is primarily used as a tool to digitally archive the choreographer's aesthetic choices. Instead, we focus on the environmental dimensions of the technology, as the impacts of energy-use and resource-depletion by AI infrastructures are rarely addressed in choreographic practices involving AI. *Heat Work*, therefore, adopts a critical perspective on choreographic decision-making with AI methods, using the key factors of temperature and computational energy as a lens to analyze extractivism. Furthermore, *Heat Work* considers choreography as a cultural medium for analyzing and educating ML algorithms, exploring how algorithms can be re-configured through dance movement to address specific variables related to thermality, energy and resources. This approach has the potential to open up a broader field of "critical" choreography that integrates AI and ecological concerns.

In the following sections, we present the methodology for *Heat Work*. First, we describe the initial selection of Santhali dances followed by motion capture and data classification. The goal in this process was to examine the links between the dance movements, computational workloads, heat generation and energy consumption. Next, we explore and analyze the selection of a modeling technique and the application of ML respectively. From these we gather our results and discuss the implications of our methodology in the concluding section.

3. Selection of Santhali Dances

We examined various dances from the tribal region of Jharkhand, focusing mainly on Santhali dances performed during seasonal festivals. These dance movements not only served as the subject of analysis but also provided a critical perspective on political and colonial issues intertwined with the environmental effect of extractivism and the realm of art. These dances offer movements inter-linked with extractivism and environment. Dances are usually performed with "songs for various festive occasions, especially for the spring and harvest celebrations, but also to compositions rendered at the turning points in the life of individuals, such as initiation and marriage." (Kuckertz 1998). "Being in the lap of nature, the tribals' cultural performances like

songs, dances, proverbs, riddles are reflections of their interaction with the environment.” (Bhattacharjee 2011). We believe that environmental behavior is deeply rooted in the intangible cultural heritage of these tribal communities and is reflected through their aesthetic language of the performing arts. According to Curtis, Reid & Reeve “being involved in a performance or in creating art helps consolidate one’s beliefs or reinforces them and can influence aspects of environmental behavior. This is achieved – “through evocative representations of the environment while others achieve it by being in the natural environment itself.” (Curtis, Reid & Reeve 2014).



Figure 1. Santhali dance during Baha festival. Image Rights: CC BY 4.0

The principal investigator and first author Bhowmik’s cultural origin naturally steered the research towards Jharkhand region of India where he was born and raised. To explore further, we also collaborated with artist and performer Vishnu Vardhani Rajan who hails from the indigenous region in Telangana in southern India. Rajan has been studying the comparative impacts of mining in Singareni coal fields in Telangana vs Kittila in Lapland, both indigenous lands, through her artistic research. The choice of their own culture as the epicenter linked the project with a case of a widely embodied movement practice exposed to (or surrounded by) high extractivist activity, with a sensitive and personal undertone. Santhali dance is categorized as folk. As opposed to classified Indian dance forms (e.g. Bharatanatyam, Odissi, Kathak, etc.) the inherited kinetic knowledge of folk dance is detached from virtuosity and the idea of an artistic performance that caters to an audience. The examination of Santhali dance investigates the possibility of it being a porous practice, in which the potential impact of extractivism to the local community can be observed through the embodiment of the dance. Our research takes this speculative position as a basis for further investigation. We do not claim this to be absolutely proven in current discourses.

Much of the research on Santhali people was conducted via the internet (e.g. using the search term “Santhali dances” on YouTube) as the project was based in Helsinki, Finland. Although the internet facilitated access to information, it was not able to fully bridge the project with the local Santhal community. Whilst the research group employed and experimented technologically with Santhali dances, there was no direct engagement with the local dancers. The internet and remote research created a blind spot towards active contribution to the culture in question, by producing research that seemingly does not respond to the community's immediate needs. The choice of Santhali dance was met with questions on cultural appropriation, to which Rajan responds:

Our work does not erase Santhal dances but focuses on the mining issues in the region. We haven't claimed to replicate the exact steps or appropriate the dances without proper credit. However, we did play with the gaze. The multiple layers of gaze – an urban Indian interpreting a tribal dance, reinterpreted by technology – create a palimpsest. We were cautious to avoid using cultural imagery or materials like clothing.

In our research we included eight to ten Santhali dance forms that are accompanied by drums and flute. These are: *Baha*: performed during *Baha* festival; *Langre*: conversational dance (Akhra: platform, arena); *Dong*: dynamic performance with jumps (only during events such as weddings or birthdays); *Dahar*: performed on roads; *Dantha*: Martial, jumping and battle movements, during *Sohrai* festival, after *Dussehra*; *Patah*: group dance, dancing in a line and performed in fairs; *Rinjha*: Harvesting sacred dance; *Dabung*: a casual and contemporary dance; and *Dasai*: martial, battle movements, with peacock feathers in turbans, celebrating freedom fighting. Please note that this list is not comprehensive and there are potentially other dances which we have not come across that are yet to be documented. In some cases, the dances are also cross performed between other tribal groups such as the *Munda*, *Oraon*, etc. As such, for our choreographic experiment, the performer familiarized herself with the readily available documentation of the dances from online archives, followed by rehearsals of each movement. Rajan selected moves based on shared similarities across the different Santhali dance forms. As the performer describes:

“The selection process was intuitive. The video captures snippets of the Jatar, a village celebration, where the group in the video engages in rhythmic talk-speech about "the hool against the zamindars" (landlords of the 1855 rebellion). The music, familiar to me, features older percussion instruments. I chose this video because it contrasts sharply with the study methodology of Heat Work, adding an intriguing layer to the entire project.”

After the selection, the authors choreographed the preliminary routine of movements in the lab. This routine composed of ten discrete movements were sequenced in order of a coherent performance. These distinct movements were then selected for motion capture.

4. Seeking the Heat and Energy of Motion Capture

It is often required in motion capture to amplify or exaggerate a movement so all its quality nuances can be seen digitally. However, we considered this requirement of the digital medium to be conditioning the dance and perhaps alienating it from its original form, therefore we did not adjust the movement intensity to motion capture standards. One could argue that this choice might also alienate the dance as it is not pursuing a faithful digitalization of the form. With our decision to resist kinetic adjustments, we are pouring the weight of deficient capturing onto the technological medium and not onto the dance form. For Rajan, this was their first experience of motion capture. She describes the process of capturing as solo, what is supposed to be a

communal practice, as a coat of criticism towards the “increasing individualism and loss of community”, without idealizing the challenges of the tribe. According to her:

“The many layers of absence were captured: the lack of community members to dance, the gaps in the land, language, and technology, the absence of the Santal rebellion in our education system that exist only as songs in oral history.”



Figure 2. Motion capture of ten *Santhali* dance movements using sensor body suit in the lab

We conducted the capture process using a full-body sensor suit and associated software. These movements were stored in the Biovision Hierarchy file format, a format for motion capture data. In addition to this, we had access to complementary spreadsheets in XLSX format, which documented various joint positions over time series. Complimentary to the motion capture data and its variations, we monitored energy use and thermal energy usage of GPU during motion capture sessions using Open Hardware Monitor, a software application for recording energy consumption and heat generation of computation.

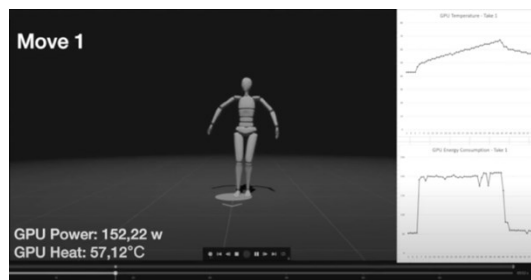


Figure 3. A motion capture movement with graphs of GPU heat and energy consumption

The original sensor dataset comprised 47 explanatory variables and 2 response variables, creating a dimensionality of 47x2. This high dimensionality poses challenges, complicating algorithm application and demanding substantial computational resources. Additionally, for meaningful data interpretation in various applications, dimension reduction methods are often necessary. In addressing this challenge, our approach involved employing dimensionality

reduction techniques, specifically focusing on investigating correlations between energy consumption and temperature for each dance movement and among joint positions. A significant challenge in dimensionality reduction is selecting variables for retention while discarding those with minimal impact on the analysis. In our study, concentrating on the computer's GPU (Graphic Processing Unit)'s energy consumption as the representative variable played a pivotal role in significantly reducing the dataset's dimensionality. This not only supported the computational efficiency of our analysis but also heightened its interpretability. The deliberate reduction in dimensionality streamlined the computational aspects and enhanced the overall interpretative value of the findings.

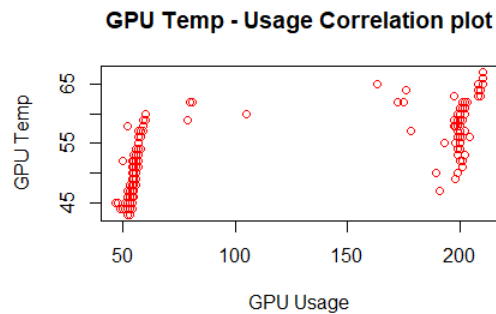


Figure 4. GPU Temperature vs Usage correlation plot

An intriguing finding during our analysis was the conspicuous linear correlation observed between energy consumption and temperature (see Figure 4). This correlation suggested a close link between changes in temperature and energy consumption. However, we acknowledge temperature can be influenced by many external factors, such as cooling systems and ambient temperatures, which may introduce noise and confounding variables into the analysis. GPU energy consumption, conversely, demonstrated stability compared to temperature, as it was more controlled within the motion capture system, thereby providing a reliable and consistent metric for our analysis. Considering these findings, we resolved to select GPU energy consumption as a representative variable, enabling us to delve into the fundamental relationship between energy consumption and dance movements. Thus, by opting for GPU energy consumption, we were empowered to scrutinize the impact of different dance movements on energy consumption. This choice facilitated an exploration into how the intensity and complexity of specific dance moves influenced the energy requirements of the motion capture system.

5. Modelling for Heat and Energy in Dance Movements

ML methods allow computers to learn from data and expand their knowledge as the dataset expands (Taye 2023). Our goal was to use ML to gather valuable insights, ranging from heat levels to more intricate energy and ecological elements embedded within each dataset. Therefore, the continuous learning process of ML algorithms was a crucial theme in our investigation. We investigated the internal dynamics of the algorithmic learning process, emphasizing how each

new set of training data influences the behavior and decision-making processes. We aimed to train the model to forecast energy consumption and temperature for Santhali dance movements accurately. This predictive capacity was a way to understand and optimize energy aspects linked to movement within the dataset. The model's ability to forecast these facets holds the promise of exposing previously overlooked heat patterns and contributing to a richer comprehension of movements.

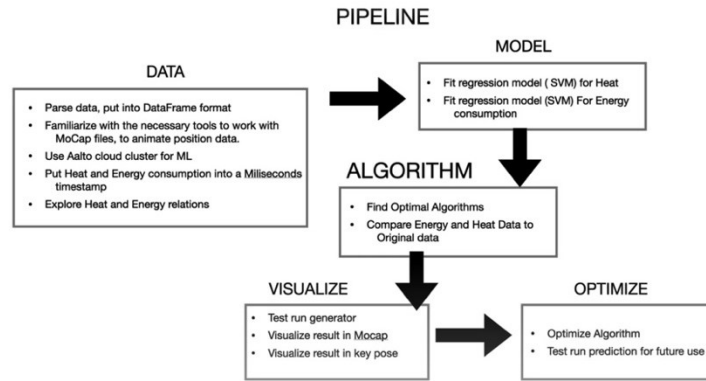


Figure 5. Pipeline of the Project

We began with an initial exploration of various classification training options to identify the most effective algorithm. Options considered were classification methods including Support Vector Machine (SVM), logistic regression, k-nearest neighbor, and random forest. Both logistic regression and k-nearest neighbor algorithms proved less effective when it comes to complex high-dimensional data, while random forest is effective but difficult to analyze due to assemble of trees. We ultimately decided to use (SVM) algorithms for the training process. This choice was guided by several factors that align with *Heat Work's* focus on extractivism. Firstly, SVM is prevalently use the domain of mine extractivism, thus “reflecting the tangled processes associated with this industry.” (Hyder, Siau and Nah 2019). Secondly, SVM's regression and classification models offer essential flexibility and adaptability in their city to handle various data types and tasks. It is particularly valuable for capturing the intricate movements and energy dynamics inherent in dance poses. Additionally, SVM is easy to interpret, as “the interpretability owing to its geometric approach in determining the hyperplane with maximum margin between classes.” (Witten et al. 2017). The visual clarity of the decision boundary, reliance on support vectors, and the transparent influence of kernel functions contribute to the model's interpretability. Finally, SVM is a supervised learning model, “a pivotal characteristic that contributes to the transparency and interpretability of the training process.” (Awad and Khanna 2015). In the realm of ML, “transparency is often a critical consideration, especially when dealing with complex algorithms that might be perceived as “blackbox.”” (Sharma, Kumar, and Chuah 2021). By leveraging labeled data, SVM provides greater clarity and insight into the decision-making process. All these factors determined SVM's appropriateness for Heat Work.

Our final SVM model underwent training using each dance frame for 20 milliseconds, treating them as features, and assigning labels of High, Medium, or Low energy consumption. This classification allowed us to comprehend how different dance movements were embodied,

highlighting the intensity of energy associated with each move. At the developmental stage of the experiment, it was necessary for the model to construct a vocabulary which described the dance moves based on their energy consumption criteria. The followed method for movement categorization did not adopt any Santhali terminology or theory, and its purpose was to offer an alternative way of thinking around movement in any form of dance. This approach is expected to raise questions on the unintentional erasure of culturally significant methods of categorizing set movement by Santhali people, and their eradication in view of advancement or new knowledge. We are aware of this discourse and the potential contribution and value of cultural inclusion, yet the involvement of Santhali theory into the task of movement categorization would lead the project to an unfeasible timeline and resource expenditure. Therefore, the project was limited to the quantitative aspects of energy and heat in Santhali dance movements.

However, our structured categorization still preserves and documents the diversity of movement by joints locations, ensuring that its unique forms are recognized later in the study. From a technological standpoint, the classification of dance movements into high, medium, and low energy levels is crucial because machine learning models lack an inherent understanding of energy consumption levels. The classification into high, medium, and low energy is derived from measurable and objective data of GPU energy consumption and is informed by established standards for GPU power usage (Gough, Steiner, and Saunders 2015). These metrics provide a framework to quantify energy expenditure irrespective of the dance form. This classification enables the models to recognize patterns in energy usage associated with different dance moves, which is essential for studying the relationship between movement and computational energy consumption. Our primary aim in this study is to explore the choreographic framework and examine heat energy consumption in the context of movement. The use of classification serves as a methodological tool to categorize and analyze patterns in data, not to generalize about or classify the dances themselves. By focusing on the data associated with energy usage rather than the dances, we ensure that the framework aids in understanding computational and thermal energy consumption in relation to movement.



Figure 6. Still image of new predictive choreography from ML training

To construct a choreography of movements prioritizing sustainability and efficiency, we had to curate a set of movements associated with low energy levels. The modeling process proceeded to the exclusion of frames associated with High and Medium energy levels, with a deliberate focus on preserving solely those exhibiting Low energy levels. The identified Low energy frames were then cataloged in a list, ensuring the preservation of the original sequencing of movements. Consequently, we obtained a comprehensive list of frames, each representing a distinct body pose in the format of Cartesian coordinates x , y , and z denoting various joint locations in

numerical data. These poses were chosen using the ML model to minimize GPU processing costs and were organized to feasibly represent the human body movement. To augment future applicability and visualization capabilities, the RmoCap tool was employed to transform these frames into BVH (Biovision Hierarchy) files. This process not only visualizes the outputs but also prepares them for integration into other choreographic projects. This approach ensured that the dataset was not only optimized for computational efficiency but was also versatile and readily adaptable for future creative and analytical experiments. The final SVM model operates as a multi-classification system, swiftly trainable and consuming an average amount of energy without oversimplifying the inherent complexity of the problem. The algorithm's ease of interpretation and analysis meets all the predefined goals set for the ML problem at hand.

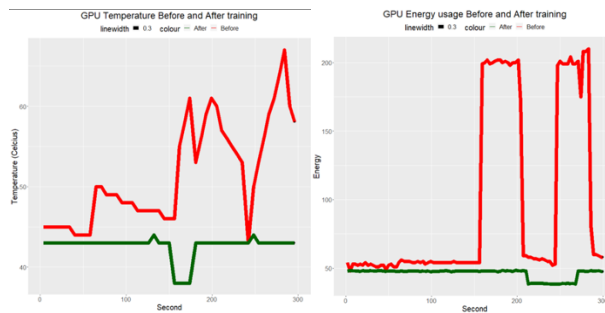


Figure 7. GPU Heat and energy use (a) before and (b) after ML Training

Beyond move-specific predictions, the research also analyzed the computational and thermal energy characteristics of the ML model itself. Figure 7 depicts the energy and heat during training and output that contribute to an energetic understanding of the ML process. These graphs offer a comparative analysis of energy and heat characteristics in relation to the original set of dance moves. From this data trained in our ML model by GPU usage and energy consumption, we were able to generate alternative routines. These new routines can be further acted upon by the performer to generate other movements which can be then fed into the ML model as training data.

6. Conclusion: Choreography as an Ecological Enquiry

Heat and energy have been key elements in various cultures and are now deeply entangled with the advancing technologies of ML and AI. Additionally, AI contributes to the growing demand for the extraction of critical metals and minerals. This has resulted in large swathes of our planet being turned into extraction zones. As such, the environmental impacts are tremendous, and the social implications will be far reaching in the years to come. In this article, we have focused on the extraction zone of Jharkhand in India and its tribal dances, and we wish to draw attention to the still surviving folk dances practiced here amidst all the mining and environmental degradation taking place. We are not entirely sure how much of the environmental change gets embodied into the current iterations of the dances, and how much the dance culture is sensitive and malleable to such changes. A limitation of our project has been the lack of a qualitative study since we have focused on data analysis and simulation towards our goals of heat and energy.

However, we believe a comprehensive investigation of Santhali dance movements, both subjectively and quantitatively in relation to the environment could yield further insights in future studies. Following our selection of Santhali dance movement, we have presented an experimental methodology of choreography with ML. The methods and processes in this article offer several contributions to the field of choreography with AI.

Primarily, *Heat Work* introduces methods to examine energy consumption and computational heat of dance movements by motion-capture and in ML. During the analysis of motion-captured movement data we uncovered a strong correlation between changes in temperature and energy consumption. GPU energy use was established as a representative variable, enabling us to go deeper into the fundamental relationship between energy consumption and dance movements. In the ML stage, our model yielded insightful predictions regarding the energy associated with each dance move, which we categorized into high, medium, and low energy consumption levels. This analysis extended to pose-specific energy consumption predictions, illustrating the energy and heat dynamics of ML during training and output. Further, the transparency of the classification model's capacity to differentiate between energy consumption levels enhanced our understanding of using body movements to assess the environmental impact of ML. "This transparency not only aligns with ethical considerations but also empowers individuals to comprehend and engage in discussions about AI, repeat actions, optimize outcomes, or choose to disregard them." (Liangru 2022) Furthermore, it enables a participatory approach to AI, "where users are not passive recipients but active participants in the decisions made by intelligent machines." (Busnatu et al. 2022). Together they offer a transparent algorithmic decision-making and versatile understanding of the machine energy dynamics within a choreographic framework, facilitating both analysis and discussion. This approach makes energy consumption and heat influential elements for choreography. By focusing on low-energy poses, we may introduce a creative and energy-conscious praxis that highlights the often-overlooked costs of energy in intelligent performance.

This introduction of heat and energy as a factor for choreographic conditioning is a key contribution. In the context of environmental choreography, *Heat Work* offers the possibility to include the factual data of extractivism within the creative process. It links dance to the awareness of computational expense, tying it to extractivism, and thereby combining these approaches into a choreographic tool for decision-making applicable to any nature of dance. In a way, it introduces a new method of environmental art making, where machines and artists can co-choreograph material that responds to the objective data of energy consumption and the ecological aftermath. The goal of our project is to advocate for a choreographic future where intelligent performance making is informed and concerned with the environmental cost of its practice. Lastly, if anything, *Heat Work*'s focus on thermality and energy, overlapping dance and computation, aims to influence the discourse on AI choreography towards the ecological. We believe choreography to become an ecological enquiry, it must deal with the thermocultures of contemporary intelligent performance and AI's environmental dependencies to address broader questions of ethics and environmental justice.

Acknowledgements

We thank the Research Council of Finland (Funded project: “Terra-performing: Unfolding Extractivism by Intelligent Performance Research”, 2022-27) and the Just-AI Project (just-ai.net) at the London School of Economics. We appreciate the technical assistance of Roberto Pugliese in the motion capture experiments at the digital studio of the Academy of Fine Arts Helsinki.

References

Awad, Mariette, and Rahul Khanna. 2015. *Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers*. Springer nature.

<https://library.oapen.org/bitstream/handle/20.500.12657/28170/1/1001824.pdf>.

Babiracki, Carol. 2000. “‘Saved by Dance’ The Movement for Autonomy in Jharkhand.” *Asian Music* 32 (1): 35–58.

Bhattacharjee, Somenath. 2011. “Folk Culture and Environmental Sustainability.” *A Biannual Journal of South Asian Studies* 4 (2).

<https://www.pondiuni.edu.in/files/publications/IJSAS/IJSAS-18012011.pdf#page=87>.

Busnatu, Ștefan, Adelina-Gabriela Niculescu, Alexandra Bolocan, George ED Petrescu, Dan Nicolae Păduraru, Iulian Năstasă, Mircea Lupușoru, Marius Geantă, Octavian Andronic, and Alexandru Mihai Grumezescu. 2022. “Clinical Applications of Artificial Intelligence—An Updated Overview.” *Journal of Clinical Medicine* 11 (8): 2265.

Crawford, Kate. 2021. *The Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. Yale University Press.

Crawford, Kate, and Vladan Joler. 2018. “Anatomy of an AI System: The Amazon Echo as an Anatomical Map of Human Labor, Data and Planetary Resources,” *AI Now Institute and Share Lab*, Sept. 2018.

Cuan, Catie. *OUTPUT*. 2020. Accessed December 5, 2024. <http://catiecuan.com/output>

Cuan, Catie. 2021. “Dances with Robots: Choreographing, Correcting, and Performing with Moving Machines.” *TDR* 65 (1): 124–43.

Curtis, Genevieve. 2020. “Dances With Robots, and Other Tales From the Outer Limits.” *International New York Times*, Updated November 7, 2020.

<https://www.nytimes.com/2020/11/05/arts/dance/dance- and-artificial-intelligence.html>

Curtis, David J., Nick Reid, and Ian Reeve. "Towards Ecological Sustainability: Observations on the Role of the Arts." *SAPI EN. Surveys and Perspectives Integrating Environment and Society* 7.1 (2014).

- Girschig, Bastien. "Living Archive by Wayne McGregor." Google Arts & Culture Lab, November 2019. Online. <https://experiments.withgoogle.com/living-archive-wayne-mcgregor>
- Gough, Corey, Steiner, Ian, and Winston Saunders. 2015. CPU Power Management. In: *Energy Efficient Servers: Blueprints for Data Center Optimization*. Springer Nature, Berkeley, CA. https://doi.org/10.1007/978-1-4302-6638-9_2
- Hao, Karen. 2019. "Training a Single AI Model Can Emit as Much Carbon as Five Cars in Their Lifetimes." *MIT Technology Review* 75: 103. Online.
- Hyder, Zeshan, Keng Siau, and Fiona Nah. 2019. "Artificial Intelligence, Machine Learning, and Autonomous Technologies in Mining Industry." *Journal of Database Management (JDM)* 30 (2): 67–79.
- Kuckertz, Josef. 1998. "Songs of the Santals." *Indian Musicological Society. Journal of the Indian Musicological Society* 29: 94.
- Lerner, Sarah. 2022. "Genealogies of Environmental Media: Feminist Art and the Choreographic Body in Social Works." *Media+ Environment* 4 (1). <https://mediaenviron.org/article/35470.pdf>.
- Lidberg, Pontus. *Centaur*. 2020. Accessed December 5, 2024. <https://www.pontuslidberg.com/works/centaur>; <https://www.artificialmind.ai/projects-3/centaur>
- McGregor, Wayne. *Living Archive: An AI Performance Experiment*. 2019. Accessed December 5, 2024. <https://waynemcgregor.com/productions/living-archive>
- McGregor, Wayne. *No one is an Island*. 2020. Accessed December 5, 2024. <https://www.random-international.com/no-one-is-an-island-2020>
- Mukherjee, Arup. 2023. "Saranda Forest Range: A Fragile Ecosystem at the Crossroads of Development and Conservation." *Journal of Emerging Technologies and Innovative Research | JETIR November 2023, Volume 10, Issue 11*. <https://papers.ssrn.com/abstract=4646640>.
- Sharma, Ruchi. 2005. "Forest and the Tribals in Jharkhand: Post Independence Scenario." In *Proceedings of the Indian History Congress*, 66:768–77. JSTOR. <https://www.jstor.org/stable/44145889>.
- Sharma, Ritu, Arpit Kumar, and Cindy Chuah. 2021. "Turning the Blackbox into a Glassbox: An Explainable Machine Learning Approach for Understanding Hospitality Customer." *International Journal of Information Management Data Insights* 1 (2): 100050.
- Taye, Mohammad Mustafa. 2023. "Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions." *Computers* 12 (5): 91.
- Ureta, Sebastián, and Patricio Flores. 2022. *Worlds of Gray and Green: Mineral Extraction as Ecological Practice*. Vol. 11. Univ of California Press.

Witten, Ian H., Eibe Frank, Mark A. Hall, and Christopher J. Pal. 2017. “Extending Instance-Based and Linear Models.” <https://publications.polymtl.ca/51883/>.

Ystgaard, Pål, Tone Beate Gjerstad, Terje Kristoffer Lien, and Per Aage Nyen. 2012. “Mapping Energy Consumption for Industrial Robots.” In *Leveraging Technology for a Sustainable World*, edited by David A. Dornfeld and Barbara S. Linke, 251–56. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-29069-5_43.

Contributors

Samir Bhowmik is an Academy Research Fellow at the University of the Arts Helsinki.

Minh Anh Nguyen is a data science researcher. She is currently pursuing her MA in Machine Learning, Artificial Intelligence, and Data Science at Aalto University, Finland.

Lydia Touliatou is a choreographer and a performer. She received a MA in Choreography from the Theatre Academy, Finland.

Alison B Powell is Associate Professor in Media and Communications at the London School of Economics.

Vishnu Vardhani Rajan is an artist, performer, and film maker.