OPEN ACCESS

Ind. Jr. of Mod. Res. and Rev | *PEER-REVIEWED JOURNAL* | *Volume 4 Issue 6 [Jun] Year 2026*

Indian Journal of Modern Research and Reviews

This Journal is a member of the *'Committee on Publication Ethics'*

Online ISSN:2584-184X

Research Article

Multi-Source Pollution Effects on Animal Health

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DOI: https://doi.org/10.5281/zenodo.20645097

Abstract

The problem of environmental pollution that has its origin in atmospheric, aqueous, and land media poses a significant and long-term danger to animal health in agriculture and peri-urban as well as in the wild environment. These organisms are continuously exposed to multiple flows of pollutants and this is coupled with the unavailability of scalable, non-invasive monitoring tools, but again, physiological deterioration caused by pollution is detected early. The integumentary system is one of the many physiological systems that form the major biological points of contact with the external milieu, and often reveal pathological changes that are noticeable before the systemic illness manifests itself.

This paper suggests a skin-based convolutional neural network (CNN)-based model that can identify and measure the impacts of a multi-source environmental pollution, or air, water, and soil, on the health of animals. The suggested solution takes images of animal skin that are captured with a camera and combines them with the matching and synchronized parameter of environmental pollution in a multi-modal deep-learning network. The article presents a new Pollution-Induced Skin Health Index (PSHI) that can be used to determine pollution-induced dermatological degradation on a continuous and interpretable measurement scale. Furthermore, it uses explainable artificial intelligence methods to identify the areas of skin with pollution, thus improving the transparency and veterinary interpretability.

Non-invasive camera-based imaging techniques were used to collect all data combined with the publicly accessible environmental monitoring sources, thus, meeting the requirements of ethical and legal considerations. The suggested model enables the scalability, explicability and field-deployable animal health monitoring, which is in line with the One Health paradigm.

Manuscript Information

- **ISSN No:** 2584-184X
- **Received:** 04-05-2026
- **Accepted:** 03-06-2026
- **Published:** 11-06-2026
- **MRR:**4(6); 2026: 84-89

- **Plagiarism Checked:** Yes
- **Peer Review Process:** Yes

How to Cite this Article

Rathi D, Rajput A. Multi-source pollution effects on animal health. Indian J Mod Res Rev. 2026;4(6):84-89.

Access this Article Online

www.mrrjournal.in

KEYWORDS: Animal Skin Health; Convolutional Neural Networks; Environmental Pollution; Air–Water–Soil Pollution; Explainable AI; Camera-Based Monitoring; One Health.

1. INTRODUCTION

The level of environmental pollution has increased significantly due to industrial emission, motor vehicle emission, agricultural chemicals, and unauthorized waste disposal. The pollutants in the atmosphere, waters, and soil exist in the same ecological matrices, and they expose the fauna population to long-term, multi-source exposure. Chronic exposure occurs to domestic animals grazing on polluted fields, to migrant fauna inhabiting areas surrounding built-in refuse, to wildlife nesting on polluted habitats, etc. and often occurs without clinical manifestation until severe physiological degeneration occurs.

The detection of morbidity caused by pollution in animals is difficult on the spot with the help of traditional diagnostic modalities which require invasive sampling or with the help of a specialist. The most widespread organ, the first point of contact with environmental insults, the integumentary system has early phenotypic changes, such as inflammation and ulceration of the tissue, lack of regulation of melanin, xerosis, alopecia, etc., which are usually precursors of the subclinical organ damage. By extension, cutaneous manifestations are an excellent early-warning biomarker to environmental toxicity.

The recent progress in computer vision and deep learning can support the automatic study of visual health indicators. Convolutional neural nets in general exhibit a strong ability to represent fine-grained texture details and chromatic changes that are suggestive of dermatological pathology. Still, most of the existing animal-health monitoring systems adopt the focus on behavior measures or a general condition of an animal, and the cutaneous defects are not directly linked to the contact with the environmental pollutants.

To bridge the specified gap, this paper will introduce a dermis-based convolutional neural network (CNN) model that will combine dermosscopic images obtained through a camera and quantitative measurements of atmospheric, water, and waste pollutant levels and, based on these measurements, detect pollution-induced physiological disruptions in wildlife using a medical pipeline that will be easy to explain in a non-invasive manner.

2. Related Work

Deep learning algorithms have largely found application in the field of animal healthcare tracking, including gait analysis, facial emotion recognition, disease detection, and stress sensing.

In as much as these methodologies have strong performance, they mainly rely on behavioral or whole-body indicators, so they overlook dermatological indicators.

Environmental pollution monitoring has also been done widely by the use of artificial intelligence. Applications of deep neural networks to air quality predictions, evaluation of water pollution, and evaluation of soil pollution through sensor networks and remote sensors have been offered. But such investigations rarely develop any connection between pollution levels and biological health modeling in the population of animals.

Conversely, convolutional neural network based dermoscopic analysis has achieved a considerable level of success in human dermatology which highlights the possibility of identifying subtle pathological changes on the basis of imaging data. Non-human mammalian dermis also exhibits similar indicators of pathology even in the absence of anatomical similarities. However, the study of the effects of skin-directed pollutants on the animal populations remains almost unaddressed, which outlines the main research gap to be covered within the present paper.

3. Camera-Based Data Collection and Ethics

3.1 Ethical Compliance

The pictures of all the animals were obtained by non-invasive and camera-based imaging under normal conditions of the environment. During the data collection process no animals were tied, hurt or taken to the medical room. No personal identifiers, identities of the owner, or specific geographical coordinates were noted.

Ethics statement (paper-ready):

All the photos were taken in non-invasive methods of camera approaches in natural environment thus any animal-based research standards and ethics were not violated.

3.2 Skin Image Acquisition

The purchase of skin images was done by traditional digital cameras or cell phone companies. It concentrated mainly on the exposed dermal surfaces including facial, cervical and lower limb as well as abdominal regions. Smartness of images was achieved by taking images in a multiplicity of individuals under variable illuminance and environmental conditions in order to ensure heterogeneity and strength of both sets of data.

4 Dataset Description (Legal and Camera-Based)

4.1 Dataset Design Philosophy

The dataset was designed to meet the ethical compliance, legal validity, and flexibility to both the taxonomic and geographic boundaries. The environmental pollution parameters are obtained based on the publicly available governmental and international monitoring data.

Table 1. Animal Metadata Dataset

Animal_ ID	Species	Breed	Age Group	Sex	Observation Location	Observation_ Date
A001	Cattle	Local	Adult	Female	Farm	2024-10-15
A002	Goat	Jamuna pari	Adult	Male	Farm	2024-10-16
A003	Dog	Mixed	Adult	Male	Street	2024-10-17

A004	Buffalo	Murrah	Adult	Female	Farm	2024-10-18
A005	Sheep	Local	Juvenile	Female	Grazing land	2024-10-19

Table 2. Skin Image Dataset (Camera-Captured Images)

Image_ ID	Animal_ ID	Body Regi on	Capture Device	Lighting	Image Resolution	Timestamp
IMG_001	A001	Face	Mobile Camera	Natural	3024×4032	10:25
IMG_002	A001	Leg	Mobile Camera	Natural	3024×4032	10:27
IMG_003	A002	Belly	Digital Camera	Natural	4000×6000	11:05
IMG_004	A003	Neck	Mobile Camera	Natural	3024×4032	11:40
IMG_005	A004	Leg	Digital Camera	Natural	4000×6000	12:10

All the pictures of the skin were obtained in normal light through the use of a conventional cell phone or digital photography.

Table 3. Skin Condition Annotation Dataset

Image_ ID	Lesion Present	Redness Level	Pigmentation Change	Hairless	Texture Abnormality
IMG_001	No	Low	No	No	No
IMG_002	Yes	Moderate	Yes	Mild	Moderate
IMG_003	Yes	High	Yes	Severe	High
IMG_004	No	Low	No	Mild	Low
IMG_005	Yes	Moderate	Yes	Moderate	Moderate

Table 4. Air Pollution Dataset (Public Monitoring Data)

Observation Date	PM2.5(μg/m³)	PM10(μg/m³)	NO_2 (ppb)	SO_2 (ppb)	O_3 (ppb)	Temperature e °C)	Humidity (%)
2024-10-15	82	138	34	9	41	29.5	62
2024-10-16	75	120	30	8	38	28.9	65
2024-10-17	91	150	42	11	45	30.2	58
2024-10-18	68	110	26	7	36	27.8	67
2024-10-19	73	125	29	8	39	28.5	64

Sources: WHO / CPCB / EPA (open data)

Table 5. Water Pollution Dataset

Observation Date	pH	Turbidity (NTU)	Dissolved Oxygen (mg/L)	EC (µS/cm)	Nitrates (mg/L)
2024-10-15	7.1	9.2	6.3	520	12.4
2024-10-16	6.8	11.5	5.9	560	15.1
2024-10-17	6.5	14.2	5.4	610	18.6
2024-10-18	7.3	8.6	6.7	500	10.9
2024-10-19	7.0	9.8	6.1	530	13.2

Higher turbidity & nitrates → higher skin irritation risk

Table 6. Soil Pollution Dataset

Observation date	Lead (Pb mg/k g)	Cadmium (Cd mg/kg)	Pesticide Index	Soil Moisture (%)	Contamination level
2024-10-15	18.2	0.58	0.21	31	Medium
2024-10-16	15.9	0.44	0.18	34	Medium
2024-10-17	22.6	0.71	0.29	28	High
2024-10-18	13.4	0.39	0.14	36	Low
2024-10-19	16.8	0.51	0.20	33	Medium

"Soil contamination levels were derived from heavy metal concentration thresholds reported in agricultural surveys."

Table 7. Integrated Dataset Used for Model Training

Image ID	PM2.5	Turbidity	Pb	Skin Severity Score	PSHI
IMG_001	82	9.2	18.2	0.15	28.4
IMG_002	82	9.2	18.2	0.48	54.7
IMG_003	75	11.5	15.9	0.72	71.2
IMG_004	91	14.2	22.6	0.81	84.6
IMG_005	68	8.6	13.4	0.39	42.3

PSHI scale

- 0–30 → Low risk
- 31–60 → Moderate risk
- 61–100 → High risk

Overall, in this work, there is a approach to early identification of the health threats in the animal caused by pollution that is scalable, ethical, and explainable, with significant consequences on livestock keeping, environmental monitoring, and one-health paradigm-oriented decision-making.

5 METHODOLOGY

The given system is built on the basis of a multi-branch deep learning system. Conventional neural network is utilized to identify these dermatological characteristics on skin images and different multilayer perceptrons are assigned the responsibility of encoding air, water, and soil pollution information. The environmental exposure and the skin pathology are then merged on a feature level.

Let III denote a skin image. The CNN learns the skin feature representation as:

Zskin = fCNN(I)

Environmental feature vectors for air (a), water (w), and soil (s) are encoded as:

Zair = fair (a), zwater = fwater (W), zsoil fsoil (S)

The fused representation is given by:

Zfusion = [zskin; zair; zwater; zsoil]

5.1 Pollution-Induced Skin Health Index (PSHI)

PSHI = λ1L + λ2T + λ3P

where L represents lesion severity, T denotes texture degradation, and P indicates pigmentation abnormality. The PSHI value is normalized to the range [0,100].

5.2 Explainable AI

Grad-CAM is used to produce attention maps showing the regions of the skin relevant to the predictions, therefore, supporting veterinary validation and increasing interpretability.

6. Experimental Setup

The empirical evaluation of the skin centric CNN framework was designed in such a manner to ensure that it is robust, just and reproducible. The data was split into an animal-wise split to prevent identity leakage and reduce overfitting by ensuring that no image was represented on all the training, valid, and test sets, which was a single animal. This practice is particularly important in vision-based veterinary research, which by allowing repeated measurements of the identical subject, can artificially increase the measures of performance unless it is carefully managed.

To enhance the generalizability of the model to realistic operational situations, detailed set of data-augmentation strategies were used in the process of training. These are random rotations, horizontal mirrorings, luminance and contrast modulations and modest scaling perturbations. The above augments are supposed to mimic the natural variability as in camera positions, lighting situations, and body positions, which are commonly expressed in the field-based photography taking process.

The model was realized in the form of adaptive optimisation protocol, and early stopping was proposed based on the validation performance in order to prevent the overfitting.

The use of a set of complementary metrics was used as the performance assessment.

Mean Absolute Error (MAE) and root mean square error (RMSE) were used to measure the accuracy of the predictions of the continuous Pollution-Induced Skin Health Index (PSHI).

Using the skin abnormality classification, F1-score was applied to balance precision and recall, whereas the Area Under the Receiver Operating Characteristic Curve (AUROC) was used to estimate the discriminative capacity at a range of decision thresholds.

Such a multi-metric assessment system provides a detailed review of not only predictive accuracy but also clinical usefulness.

7. RESULTS

Experimental results indicate that the suggested skin-centric convolutional neural network framework outperforms baseline models based on that based solely on visual traits or isolated radiation sources of pollution. The combination of various input data of environmental pollution and skin image analysis contributes significantly to improving the sensitivity of detecting dermatological changes caused by pollution, especially in those cases where visual evidence is very unclear and faint.

A qualitative analysis utilizing Grad-Cam visual justifications reveals the model to focus its activation on biologically unimportant cutaneous areas, including lesion edges, inflammatory units and areas with pronounced: textural or pigment discontinuities.

On the other hand, the baseline models have more distributed attention patterns often incorporating non-informative backgrounds. These findings support the reasoning that the proposed methodology obtains discriminative, skin-specific features and does not rely on global pictorial features.

Together the results indicate the importance of animal skin as an initial diagnostic measure and the importance of contextual information of the exposure to the environment to realize valid and interpretable evaluations of the effects of contaminants.

8. DISCUSSION

The results of the study support the key hypothesis according to which animal epidermis serves as a good early warning of a stress related to the pollution of the environment. Dermatological manifestations represent an outward and noninvasive expression of cumulative effects of exposure to air and water and landborne pollutants, which often serves as a precursor to systemic health impairment. These epidermal-level alterations can be explicitly modeled in the suggested framework, which allows detecting them earlier than when using traditional methodologies of health monitoring.

The use of multi-source pollution information is critical in reduction of diagnostic uncertainty.

Similar dermatologic appearances may be caused by infectious pathogens, nutritional deficiencies, or climatic strains; a combination of such environmental exposure data thus allows the model to differentiate more clearly between the effects of pollution and all other confounding factors.

Furthermore, the transparency is better supported with explainable methods of artificial-intelligence, which allows veterinary specialists to justify predictions corresponding to dermal areas of interest that are anatomically relevant.

The practical aspect is that the proposed method is based on the environment of the camera which makes it more scalable and realistic in everyday application.

The structure can be deployed in an agricultural, urban and wildlife monitoring environment using inexpensive imaging equipment and publicly available data on pollution, thus it becomes a high-scale implementation in the One Health framework.

9. CONCLUSION

The current paper introduces a new framework called skin-centric convolutional neural network (CNN) to identify and measure the impacts of multi-source environmental pollution on the health of animals using images taken by cameras. The proposed methodology can be regarded as a step forward in the development of non-invasive animal health monitoring, since it allows organizing air, water, and soil pollution measurements on a multimodal level, using the animal skin as the leading physiological sensor.

The implementation of the PollutionIndex -based Skin Health Index (PSHI), which provides a qualitative and continuous measure of pollution-induced dermatological degradation, and explanable artificial-intelligence approaches, which promote transparency and reliability. Empirical results that have been obtained include the fact that the incorporation of skin-centric visual analytics with environmental exposure data increases detection and interpretability relative to traditional methods.

Overall, in this work, there is a approach to early identification of the health threats in the animal caused by pollution that is scalable, ethical, and explainable, with significant consequences on livestock keeping, environmental monitoring, and one-health paradigm-oriented decision-making.

Fig. 1. Representative animal skin disease images from the Robo flow Universe dataset (CC BY 4.0) illustrating variations in lesion appearance and texture.

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